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Organizations and Tasks in Trade

Le Moigne, Mathilde

Princeton, NJ : Princeton University

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Organizations and Tasks in Trade

Mathilde Le Moigne

A Dissertation

Presented to the Faculty

of Princeton University

in Candidacy for the Degree

of Doctor of Philosophy

Recommended for Acceptance

by the Department of

Economics

Advisors: Stephen J. Redding, Eduardo Morales, and Alexandre Mas

May 2021

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Abstract

This dissertation consists of three essays at the intersection of international trade and labor economics. A common theme running through these chapters is the importance of firms' organization of production processes in shaping new working environments.

In the first essay (Chapter 1) I consider the response of German local employment to import competition from China — typical of inter-industry trade —, and from Eastern Europe — typical of intra-industry input-output linkages. Using administrative data for the period 1995 to 2014 paired with an instrumental variable strategy, I find that the ability to import assembled products in the context of input-output linkages increases local employment to produce the very downstream stages of production, while the associated exposure to exports of parts has a negative employment effect suggestive of offshoring behavior.

In my second essay (Chapter 2) — co-authored with Konstantin Koerner — we study the onshore task recompostion in German firms conducting foreign direct investments (FDI) in Czech Republic. Our unique dataset compiles the universe of German multinational enterprises having affiliates in the Czech Republic. We perform a difference-in-differences estimation in a matched sample, in which propensity scores are drawn from a logit model selected by least absolute shrinkage. Relative to firms without any affiliates, multinational enterprises respond to FDI with increasing intensities of headquarter activities. We find sector-specific negative effects. We compare our findings with measures of job offshorability and we find that FDI-substitutable occupations do not necessarily overlap with offshorable ones.

Finally, my third essay (Chapter 3) focuses on understanding how firms' organization is linked to individual workers' career paths. Using French administrative data, I show that plants increasingly lost their "middle layer" between 1995 and 2015, and that young workers take longer to move up the professional ladder over these years. Using a matched difference-in-differences estimation, I show that the removal of this

middle layer (fragmentation) has substantial negative effects on workers' careers, as they are 65% less likely to be promoted afterwards, despite an increase in the employing plant's value-added by 13%. Earnings responses are consistent with compensating differentials and changes in workers' rent-sharing environment.

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They say a PhD is a very lonely process but I found out it is a collective journey. I am thankful for the amazing friendship of my classmates Matthew Cocci, Emily Cuddy, Elisa Jacome, Charly Porcher, Vivek Sampathkumar, and Alexander Wise, who became my Princeton family. I could not have finished this PhD without you. I thank my friends from cohorts above me, Adrien Bilal, Damien Capelle, Anders Humlum, Federico Huneeus, Steve Mello, Hannah Rubinton, and Rowan Shi, for their mentoring and support throughout the program. Finally, I am grateful for the constant presence of my friends from France, Lucile Guénin and Béatrice Mazoyer. Thank you for commiserating with me and for always reminding me that life is bigger than a PhD.

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À Simon.

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Chapter 1

Intra- versus Inter-Industry Import Exposure and Labor Market Adjustments: Evidence from Germany[1]

1.1 Introduction

Since the seminal paper of Autor, Dorn, and Hanson 2013a on the "China Syndrome", it is well understood that exposure to import competition from low-income countries may lead to substantial local labor market adjustments above and beyond wage adjustments. In the specific context of the United States and its import of labor intensive

[1]The data basis for this contribution is the LIAB Cross-sectional model 2 1993-2014 (LIAB QM2 9314) of the Linked Employer-Employee Data of the IAB. Data was accessed via a guest stay at the Research Data Center the Federal Agency for Labor in the Institute for Labor Market and Professional Research (FDZ) and then by means of controlled data processing at the FDZ.
I am extremelly grateful to Oleg Itskhoki and Stephen Redding for their sustained giudance throughout this project. I thank Henry Farber and Alexandre Mas for helping me in accessing the data in a secure environment from Princeton University. I am grateful to all faculty members of the International Trade and Labor workshops at Princeton University for their comments and suggestions on my work. This research benefited from financial support from the International Economics Section (IES) at Princeton University. Its support is gratefully acknowledged.

products from China, Autor, Dorn, and Hanson 2013a (subsequently ADH) shed light on important labor substitution effects away from manufacturing employment. The case of the United States and its trading relationship with China is, however, quite specific for at least two reasons. First, the United States experienced a large trade deficit with respect to China over the period 1990 to 2007. This means that the import competition experienced in the U.S. from China is not offset by export flows and therefore expanding opportunities for U.S. firms in China. In their paper, Autor, Dorn, and Hanson 2013a therefore do not account for potential exporting relationships between U.S. firms and Chinese firms in these particular sectors in which there is import competition. Second, the type of goods traded between China and the U.S. are emblematic of inter-industry trade, in the sense that the goods imported from China are not a strong competitive advantage of the U.S. economy. The substitution effect that is documented is only reflecting the employment effect of import competition in these specific industries that are directly competing with Chinese products, which reduces the scope for potential positive effects of intra-industry trade.[2]

In this paper, I broaden the analysis of local labor market adjustments initiated by ADH by changing two features of the trade relationship considered: first, I consider local labor markets adjustments in Germany, the world's third largest exporter, to allow for considering the role of exports in shaping responses to import competition in the context of relatively balanced trade relationships; second, I compare import exposure from China, which is also essentially inter-industry trade in the German context, with import exposure from Central and Eastern Europe (subsequently CEE), which is typical of intra-industry trade of intermediate inputs in the context of input-output linkages.

[2] A series of recent papers emphasizes that not only trade in inputs was important in the U.S. at that time Bloom, Draca, and Van Reenen 2016, but also that there were positive employment effects of the China shock on service jobs, also in the manufacturing sectors Bloom, Handley, et al. 2019.

I find that considering these two features carefully in studying import competition effects on local labor markets matter for the estimated effects. More specifically, they interact to go as far as significantly flip the sign of the effect of import competition on employment when the trade relationship is mainly focused on intra-industry trade of intermediate inputs and semi-finished products.

My empirical framework is directly borrowed from the well-established instrumental variable strategy of ADH, and adjusted to the German context following Dauth, Findeisen, and Suedekum 2014 (subsequently DFS). I focus on the period 1995 to 2014 that saw the accession to the WTO of China and of several Eastern European countries, as well as the integration into the European Union of a large set of these countries. I exploit cross-regional variation in import exposure stemming from initial differences in sectoral specialization of commuting zones (or local labor markets), and instrument for German imports using changes in imports from China or from Eastern European countries by other high-income countries. I add to the initial regression an additional control for export exposure to these same countries constructed with the same methodology. In DFS in the context of Germany, and Feenstra, Ma, and Xu 2019 in the context of the U.S., considering a measure of export exposure allows to estimate the job-creating effect of exports. In the period that I consider, which is later than DFS in particular, the rational behind this control stems from an omitted variable bias concern. If imports and exports are systematically positively correlated because they reflect the existence of vertical integration between German firms and foreign partners, the estimated effect of the import exposure measure will capture both labor substitution in favor of low-wage workforce, and labor adjustments in favor of a specialized organization of production. By controlling for export exposure at the local level, I allow my estimates to capture the causal effect of import exposure conditional on the local labor market being particularly integrated with the country of exposition. My export exposure measure is also instrumented, as it faces the same

endogeneity issues as the traditional import exposure measure. I show that such a control has a substantial impact on the sign of the estimated employment effects in the particular context of intra-industry trade with CEE.[3]

To understand the effect of import competition on local labor market adjustments, I consider several outcome variables of interest. To first be general and compare the German context with the U.S. context, I consider the effect of import competition on local manufacturing employment as in DFS.[4] I find that import exposure to China has a negative effect on local manufacturing employment, regardless of whether or not I control for export exposure. In fact, the coefficients are almost similar in both case, and reveal that a €1,000 increase in local exposure to Chinese imports decreases manufacturing employment by about 6.5 log points. I thus confirm the labor substitution effect in the context of Germany's trade with China, although Germany has almost balanced trade with this partner, and can therefore experience positive employment effects from a strong export exposure. On the other hand, I find that controlling for local export exposure has a dramatic impact on the estimated effect of local import competition from Eastern Europe. When export exposure is not controlled for, I find that import exposure to CEE has a weakly significant yet negative effect on local manufacturing employment. However, conditional on the local labor market exposure to exports opportunities with Eastern Europe in the same industries, I find that a €1,000 increase in regional import exposure *increases* manufacturing employment by 5 log points. Conversely, conditional on comparing local labor markets with similar import exposure, I find that an increase in export

[3]Taking into account the observation made by Adão, Morales, and Kolesár 2019 that such a shift-share design may lead to over-rejection of the null hypothesis due to correlations in regression residuals across regions with similar initial sectoral composition, I use their inference method to compute my standard errors when considering the effect of import exposure without controlling for export exposure. I however instrument for both import and export exposure in the main specification. The current command does not accommodate for several endogenous variables in the computation of the standard errors. It is my hope to be able to use this inference method for the main specification in the near future.

[4]Unfortunately, the dataset I use in this paper does not allow me to go as far back in time as they do, and I cannot therefore replicate their results.

exposure to Eastern Europe decreases significantly local manufacturing employment by 17 log points.

The conjecture I make to explain my aggregate results is that trade between Germany and Eastern Europe is characterized by vertical integration within the most traded industries. As a result, the labor substitution effect usually emphasized in response to import competition is in fact driven by export exposure, which generates incentives to offshore labor. On the other hand, the ability to import assembled and semi-finished products encourages employment to produce the very downstream stages of the production process. This organization of production has been labeled in Germany as the "Bazaar Economy" Sinn 2006. A close look at the sectors traded between Germany and Central Eastern Europe confirms that the majority of the goods traded belongs to similar three-digit industry codes, and are in majority raw or intermediate inputs (such as energy and car parts).

To verify my conjecture about the "Bazaar economy" with respect to Eastern Europe, I narrow my focus to employment of specific occupation groups, distinguishing between skilled and unskilled occupations, as well as blue and white collar occupations. In this regard, my paper differentiates itself from the work of DFS not only in the time period studied, but also in the main outcomes of interest. The focus on occupation-specific employment effects both within manufacturing industries and across sectors at the level of a commuting zone allows me to verify my working hypothesis. The occupation-level employment effects of trade exposure to Eastern Europe are coherent with the "Bazaar economy" hypothesis: conditional on export exposure, import exposure to CEE increases local employment of unskilled blue collar workers, and skilled white collars occupations, both at play in the final stages of production. On the other hand, export exposure decreases dramatically employment of unskilled blue collars, which is coherent with a large offshoring of assembly jobs.

Considering differences in employment provides information on net adjustment effects. In order to understand the dynamic response of local labor *demand* from firms — which ultimately are the one responding to the labor substitution incentive generated by import competition to low-income countries — I consider separately the effect of my import exposure measure on gross entry and exit flows of these same occupation groups.[5] Gross entry flows allow me to understand the hiring pattern of exposed firms, while gross exit flows shed light on both layoffs and voluntary quits dynamics at the local labor market level. I find that the distinction between intra- and inter-industry trade is also relevant when considering not only net employment effects but overall labor adjustment dynamics. In particular, my results suggest that trade exposure to Eastern Europe has significant effects on firms' hiring patterns through increased gross entry flows of Skilled white collars, and reduced exit flows of Unskilled blue collars. On the other hand, trade exposure to China has a stronger effect on gross exit flows than entry flows, and the effects are particularly significant for the non-manufacturing sectors. Trade with China appears to increase workers turnover in white collar occupation in non-manufacturing sectors[6], and decrease mobility of blue collar workers, that are less prone to be hired while not being laid off particularly more.

I finally relate such dynamic effects with information on firms' vacancy posting, in order to confirm the demand side of this story. My results are aligned with the dynamics suggested by entry and exit flows. In particular, I find that import exposure measure from Eastern Europe generates a strong increase in vacancies posted by manufacturing establishments, while export exposure reduces them. The opposite pattern is true for China.

[5] As initial emphasized by Davis, Haltiwanger, and Schuh 1996, net employment changes conceal large changes in gross job flows.

[6] This results are coherence with what Bloom, Handley, et al. 2019 finds in the U.S.

Literature

This paper is related to a vast strand of literature that uses the shift-share analysis introduced by the seminal work of Bartik 1991 (Blanchard and Katz 1992, Card 2001, and in the specific context of international trade, Topalova 2007; Topalova 2010, Chiquiar 2008, Kovak 2013, Autor, Dorn, and Hanson 2013a, Dix-Carneiro and Kovak 2017, Pierce and Schott 2020).[7] My focus on Germany and on comparing the impact of trade exposure to China with trade exposure to Eastern Europe is motivated by the work of Dauth, Findeisen, and Suedekum 2014 to which this paper is very close. In particular, while their main outcome of interest is net trade exposure from the East, they estimate the effect of import *and* export exposure in the same specification. Focusing on the period 1988 to 2008, they find a negative employment effect of import exposure from the East, and a larger effect from exposure to trade with Eastern Europe than with China. The overall net effect of trade exposure they estimate is however positive, as they find that export exposure to Eastern Europe in this period has strong positive effects. Despite a very careful attempt at following their empirical specification as close as possible, my results are quite different from theirs. While I find similar employment effects in the context of trade exposure to China, I find opposite employment patterns in response to trade exposure to Eastern Europe. I explain this difference mainly by the difference in time periods considered: in particular, my sample does not cover the period prior to the fall of the Iron curtain and the German reunification, and spans more years after the integration of a large amount of Eastern European countries to the European Union.[8]

My analysis departs from the one from DFS by its focus on occupation-specific adjustment. Since the seminal work by Autor, Levy, and Murnane 2003 (and in the

[7] For a recent assessment of the validity of this empirical setup, see Goldsmith-Pinkham, Sorkin, and Swift 2020.

[8] In this regard, I do not exploit the fall of the Iron curtain per se as an event in my analysis, although extensively used in the related literature (e.g. Redding and Sturm 2008, Glitz 2012 or Brülhart, Carrère, and Trionfetti 2012).

context of Germany by Spitz-Oener 2006), a lot of work has been done theoretically and empirically to emphasize the role of trade in accelerating skill-biased technical change (e.g. Burstein, Cravino, and Vogel 2013, Burstein, Morales, and Vogel 2019). My results emphasize in particular the accelerated movement away from blue collars activities generated by trade exposure from China, but also nuances the traditional view that trade exacerbate the skill-premium (e.g. Cravino and Sotelo 2019) by showing that trade exposure to Eastern Europe also favors employment of low-skilled manufacturing workers.[9]

The most important contribution of this paper resides in its use of gross entry and exit flows as well as vacancy data to study more precisely the dynamics of local employment adjustments. The emphasis on the need to introduce dynamics in models of workforce adjustment to trade shocks has been most efficiently made theoretically by Artuç, Chaudhuri, and Mclaren 2010, and confirmed empirically in recent papers focused on mobility costs (Dix-Carneiro 2014, Traiberman 2019). In the context of the U.S., Asquith et al. 2019 show that at the commuting zone level, there is substantial job reallocation from the Chinese-competition-exposed sectors to the non-exposed sectors, that cannot be clearly estimated out of net effects. I show in particular that the net employment effects at the occupation level mask very different dynamics of entry and exit of workers across establishment in the context of intra- versus inter-industry trade. Moreover, by studying directly vacancy posting behavior locally, I can relate my interpretation as to the specific needs in skills and occupations generated by trade.

The paper is organized as follows. Section 1.2 provides some historical context to understand the interest of Germany as a country of analysis, and presents the data. In Section 1.3, I present in detail the empirical framework and identification strategy. Section 1.4 presents and analyze the estimated results. Finally, Section 1.5 concludes.

[9]In the specific context of German wages, a number of additional reasons analyzed by Card, Heining, and Kline 2013 are more likely to explain wage inequalities.

1.2 Data and historical background

1.2.1 Data sources

This paper combines two main data sources. The German labor market data at the regional and local industry level comes from the linked employer-employee data from the German Institute for Employment Research (LIAB QM2 9314). Information on international trade flows is taken from the international trade database at the product level provided by the CEPII (BACI 1994-2007 version).

The longitudinal IAB establishment panel survey is based on the employment statistics aggregated at the establishment level by the employment office as of June 30th of each year. An establishment is understood as "the local unit in which the activities of a firm are actually carried out".[10,11] The panel obtained through the LIAB dataset samples establishments with at least one employee covered by social security. The sample is drawn following the principle of optimum stratification according to the stratification cells of the establishment size class (10 categories) and the industry (16 to 20 categories). The panel includes East German firms since 1996.[12] Large firms are oversampled in the dataset, a caveat that can be corrected by the use of the cross-

[10] Alda, Bender, and Gartner 2005

[11] The concept of establishment in this dataset is different from the one used in U.S. datasets. In the U.S., an establishment is a physical location where business is conducted or where services or industrial operations are performed. In the Establishment History Panel at the basis of the panel used in this paper, each firm's production unit located in a county (*Kreis*) receives an establishment identifier based on an industry classification. When each production unit within a county are allocated different industry codes, or when a firm's production units are located in different counties with the same industry code, the definition of establishment coincides with that of a U.S. plant. When a firm has more than one plant within the same county associated with the same industry however, they may receive the same establishment identifier. In the remainder of the paper I use "establishment" and "firm" interchangeably as I don't have any distinction between the two in the data.

[12] In 1993, the sample started with 4,189 plants, covering 0.21 percent of all plants in West Germany (2 million) and about 9% of total employment (29 million). The sample is representative of East Germany since 1996 with 4,210 establishments representing 1.1% of all plants (391,000) and 13% of total employment (6 million). The overall sample becomes truly representative of Germany at the *Bundesland* level since 2001.

sectional or longitudinal weights constructed with the same stratification cells. The establishment information available in the IAB establishment panel includes workforce composition (number of employees by qualification and occupation groups, number of temporary agency workers), information about wage setting within a plant (overall wage bill in June of the survey year, establishment's commitment to collective wage agreements, existence of a work council), and more general information (three-digit industry, age of the establishment, corporate position of the establishment within a firm and location), but only limited information on financial variables (in particular value added and sales).[13]

One particularity of the IAB establishment panel, is that it includes information on vacancies posted within the year. To ensure clean data, I compare the raw numbers reported by the establishments with the number of vacancies posted notified to the German social security. There's a good overlap between the two, but the number of missing values in vacancies reported by establishments themselves is much larger. I therefore only use the number of vacancies reported to the German Social Security as my main measure of vacancy posting to abstract from potential measurement errors. I consider both short-term and long-lasting vacancies in order to get enough observations.[14]

Bilateral trade flows data is taken from the BACI database provided by the CEPII. The original data contains bilateral values and quantities of exports at the HS six-digit product level for more than 200 countries, every year from 1995 to 2014.[15] I focus on bilateral trade flows between Germany and two eastern markets, namely China and Eastern Europe.[16] Values are converted to euros using publicly available

[13]For a detailed description of the establishment-level data, see Table A2 in Appendix A.

[14]The distinction is made in the variables in the raw data: long-lasting vacancies are meant to be opened for at least a year, whereas short-term vacancies are posted at a higher frequency. One future exercise that would be interesting to perform is to actually distinguish between these.

[15]For a detailed presentation of the BACI database see Gaulier and Zinago 2010.

[16]This label comprises of 15 countries: Belarus, Bulgaria, Czech Republic, Estonia, Georgia, Hungary, Latvia, Lithuania, Moldova, Poland, Romania, Russian Federation, Slovakia, Slovenia, Ukraine.

exchange rate time series from the *Bundesbank* and from the Federal Reserve Bank of Saint Louis. These are then converted into euros of 2005 by correcting for the Harmonized Consumer Price Index variation.

These two data sources are merged by harmonizing industry and product classifications. I construct a crosswalk between the 1992 HS six-digit classification of products and the three-digit level German classification of economic activities (WZ1993, based on NACE rev. 1). The HS product codes are first associated with the ISIC rev. 3 classification of industries based on the correspondence provided by the World Integrated Trade Solution (WITS), and are then manually harmonized with NACE rev. 1 industry codes based on the correspondence between ISIC rev. 3 and NACE rev. 1 provided by the UN Statistics Division.[17] Unambiguous matching of products to industries is achieved in 87% of the cases. Trade values of ambiguous cases are partitioned into industries in equal proportions.

The main geographical unit of observation in my analysis is a local labor market (*Arbeitsmarktregion*). This geographical divide is constructed by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). Very similar in definition to US commuting zones, the so-called labor market regions are formed on the basis of workers' commuting flows. The labor market regions contain the urban centers of the regional labor markets with their respective interrelations. The basis for the demarcation of the labor market regions are the shares of commuting employees between two districts, subject to the following secondary conditions: the labor market regions have an employment rate of 65% or more (as defined with respect to the working-age population of the job-place rather than the residence), a degree of occupancy of these jobs with German nationals of more than 65% without any area overlaps, and finally a daily commuting time for the simple route of maximum 45 minutes.

[17] For precise explanation of the construction of the trade data, see Appendix A.

1.2.2 Historical context

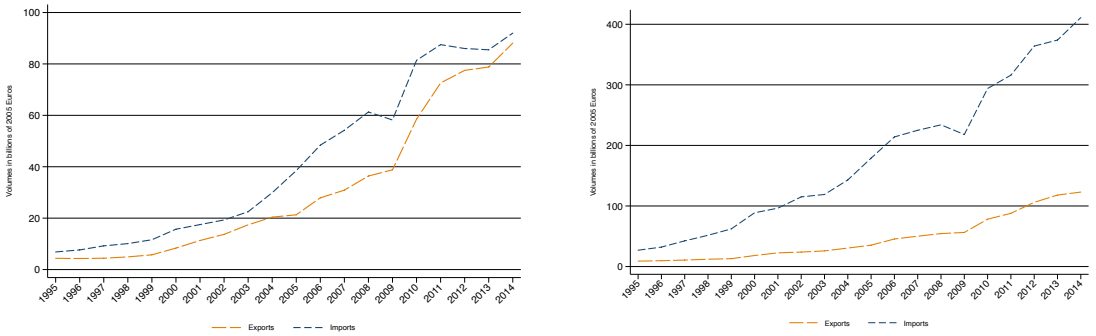
As carefully documented by Card, Heining, and Kline 2013, Germany provides an interesting setting for analyzing structural economic changes. There are two particular aspects of German historical and institutional context of interest for this paper: Germany's trade integration starting in the early 1990s, and the role of collective wage agreements and unions in local labor markets.

German trade

The focus on the period 1995 to 2014 is motivated by important changes in Germany's immediate trading partners during that time. The literature has abundantly used the accession of China to WTO in 2001 (Autor, Dorn, and Hanson 2013a, Autor, Dorn, Hanson, and Song 2014), and in particular in the German context (Dauth, Findeisen, and Suedekum 2014, Dauth, Findeisen, and Suedekum 2021). But this period is also characterized by integration of Eastern Europe in global trade, following the fall of the Iron curtain and Germany's reunification (1990). The year 1995 is characterized by the first wave of trade integration for Eastern Europe: Czech Republic, Hungary, Romania, Slovakia, Poland and Slovenia access the World Trade Organization within a couple of months, followed the next year by Bulgaria. The next wave happens between 1998 and 2001, when Kyrgyzstan, Latvia, Estonia, Lithuania, Georgia and Moldova in turn enter the WTO. In the list of Eastern European countries that heavily trade with Germany, the Russian Federation and Ukraine are the last to become members of the WTO in 2008. During the same period however, a couple of these countries that were not part of the WTO yet also signed partnership and cooperation agreements (PCAs) with the European Union. Among them we can count the Russian Federation, Ukraine, Turkmenistan, Azerbaijan, Kazakhstan, Kyrgyzstan, Georgia and Moldova who signed such agreements between 1995 and 1999. The main event

in the context of this paper is the accession of most of the Central and Eastern European countries mentioned to either the European Union, or the Schengen Agreement between 2004 and 2007. As emphasized by Dauth, Findeisen, and Suedekum 2014, Eastern European trade integration is a continuous process nonetheless characterized by notable events in the first ten years of my sample.

An interesting starting point to understand where Germany stands with respect to the eastern competition in trade, is to compare Germany's exchanges with China to those between the U.S. and China in the period 1995-2014 (Fig. 1.1).



(a) Germany

(b) United States

Figure 1.1: Germany and US trade volumes with China, 1995-2014

While imports from China increased by a close amount between the United States (nearly 1500%) and Germany (1346%) between 1995 and 2014, Germany's export to China also jumped by almost 2000% in the same period, while U.S.' exports only rose by 1380%. Starting from almost zero in 1995, German annual import volumes from China has risen to almost €40 billion in ten years, and reaches €92 billion in 2014. Despite its global trade surplus, Germany runs a trade deficit vis-a-vis China. However, this trade deficit is maintained low by an increase of German exports to China from almost zero in 1995 to nearly €89 billion in 2014. As one can see on figure (1.1a), Germany is close to balanced trade with China. To this extent, the rise of China as a world's leading source of imports led to two (almost simultaneous) changes in the German economy: the rise of import competition in manufacturing

sectors such as electronics and computer equipment as well as textile (as illustrated in Table 1.1), and the rise of market opportunities for exporters in manufacturing sectors such as automobile and specialized machinery.[18]

Table 1.1: Trade volumes with China, top-5 manufacturing sectors

Industry	2014	2010	2005	2001	1995
Imports from China					
300 Manuf. of office machinery and computers	13800	10100	7902	2130	465.5
322 Manuf. of television and radio transmitters and apparatus for line telephony and line telegraphy	7165	4076	3395	991.4	99.39
323 Manuf. of television and radio receivers, sound or video recording or reproducing apparatus and associated goods	4266	3045	2848	1138	442.7
182 Manuf. of other wearing apparel and accessories	3758	3384	1812	877.8	593.0
321 Manuf. of electronic valves and tubes and other electronic components	3251	8217	994.4	315.1	39.20
Exports to China					
341 Manuf. of motor vehicles	15800	10900	1260	486.1	235.6
343 Manuf. of parts and accessories for motor vehicle and their engines	13600	4557	1005	771.2	64.56
291 Manuf. of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines	5863	4509	1735	508.6	165.9
295 Manuf. of other special purpose machinery	5456	6013	2858	1723	1030
292 Manuf. of other general purpose machinery	4408	3243	1524	734.1	442.0

Note: Industry level trade volume in Million Euros of 2005. Sorted by trade volume in 2014.

In terms of trade dynamics, the rise of Eastern Europe is probably the most important fact concerning Germany. The sudden and unexpected fall of the Iron Curtain in 1990, and the transformation of former USSR member republics to market economies opened a large market immediately close to Germany. Overall, Germany's exports towards Eastern Europe rose by 808% between 1995 and 2014 — in majority in the automobile sector, but also in chemicals —, while imports grew by 828% — also

[18] This trend remains robust over time despite evidence of a shift of China's comparative advantage towards these same industries. In fact, German exports of motor vehicles, car parts and machinery associated with mechanical power accelerate after 2009.

in motor vehicles but also electronic components (Table (1.2)). Figure (1.2) reveals that Germany is also close to balanced trade with CEE.

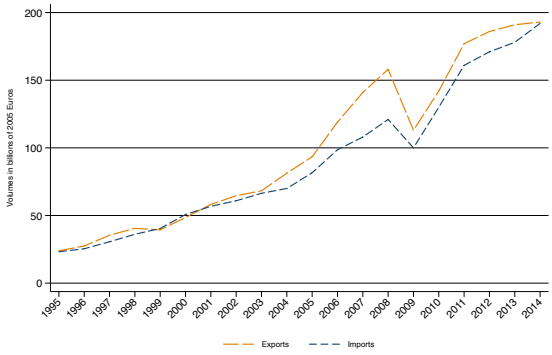


Figure 1.2: German trade volumes with Eastern Europe, 1995-2014

Table 1.2: Trade volumes with Eastern-Europe, top-5 manufacturing sectors

Industry	2014	2010	2005	2001	1995
Imports from Eastern Europe					
341 Manuf. of motor vehicles	16700	10600	7231	6655	615.1
343 Manuf. of parts and accessories for motor vehicles and their engines	16700	9491	5581	2920	438.1
274 Manuf. of basic precious and non-ferrous metals	5925	5541	3237	2593	1908
361 Manuf. of furniture	6872	4350	3464	2724	1176
323 Manuf. of television and radio receivers, sound or video recording or reproducing apparatus and associated goods	4455	4238	1748	1024	182.7
Exports to Eastern Europe					
343 Manuf. of parts and accessories for motor vehicle and their engines	15900	10800	8419	3993	499.9
341 Manuf. of motor vehicles	13400	9900	7268	5235	1693
241 Manuf. of basic chemicals	9515	6741	4130	2388	1031
295 Manuf. of other special purpose machinery	7860	6588	4650	3106	1694
252 Manuf. of plastic products	8163	5998	4303	2608	799.5

Note: Industry level trade volumes measured in Million Euros of 2005. Sorted by trade volume in 2010.

Tables 1.2 and 1.1 report the sectors with the highest import and export volumes vis-à-vis Eastern Europe and China. I focus on top-5-manufacturing sectors, even though one other big sector of trade between Germany and Eastern Europe in particular is energy. An interesting fact that arises from tables (1.2) and (1.1), —

and at the heart of this analysis — is that Germany's trade with Eastern Europe seem mostly intra-industry trade, while Germany's trade with China appears to be essentially inter-industry trade. The choice of looking at both shocks is motivated by this difference in terms of trade composition (import competition from China, and offshoring opportunities from Eastern Europe), as it raises the question of the differential impact of these trade shocks to Germany's labor markets.[19] In particular, the labor substitution effect emphasized in ADH with respect to the China shock may not be present when considering exposure to Eastern European trade.

Institutional features

In the early phase of my sample (1995-2003), German labor markets are characterized by significant wage rigidities, which justify the focus of this paper on employment flows.

Specifically in this paper, I will purposely avoid looking at German wages, for the following two reasons.[20] First, despite a fairly decentralized system, wages are often negotiated at the level of the branch, which thus restricts wages' adjustments in response to local labor market shocks. Firms being member in an employer's association can deviate from paying collectively agreed wages only by negotiating with the union at firm level, but the branch union must still agree to the result of the bargaining process. Firms who are not members of an employer's association have no restrictions in setting wages. The coverage of collective agreements in manufacturing

[19] In a related paper (Koerner and Le Moigne 2021), I study further the role of offshoring opportunities in Czech Republic for German firms and the associated adjustment of occupation-specific employment and task intensities onshore. Our results suggest that the majority of FDIs made by German firms in Czech Republic in tradable industries are associated with vertical integration. The employment effects we estimate also confirms that there are substitution of offshorable jobs in German firms. There is however to my knowledge no dataset that would allow me to control for foreign direct investment between Germany and China.

[20] A third reason that pertains to the data themselves is the fact that wages are capped in the LIAB datasets. The algorithm of wage imputation provided by Gartner 2005 and used in particular in Card, Heining, and Kline 2013 is very sensitive to the choice of the variables used for the imputation during my sample period, and yields time series of wage variance that are hard to interpret.

industries is higher than in the private service sector. The trend towards the end of the sample is however to a decrease of collective agreements, and higher wage flexibility.[21] Second, the introduction of so-called minijobs and thus "mini-wages" with the Hartz Reforms in 2003-2005 provided firms with a margin of wage adjustment through adoption of specific contracts, rather than incumbent workers' wage changes.

As a result, the key outcomes of interest in my analysis will be worker in- and outflows from German establishments. It is therefore worth mentioning two aspects of German institutions that may affect workers' mobility. One particularity of German labor markets is the role of the vocational training system (in particular for blue collar job): training duration can last between two and three years, so that such training represents a large investment for German establishments. As a result, young blue collar mobility is reduced, as establishments try to amortize their human capital investment. Industry-wide collective agreements also protect young blue collar workers by guaranteeing their position for at least one year after the training in many branches (Alda, Bellmann, and Gartner 2005).[22] Another important feature of German labor markets is the strong protection of *insiders*, which puts Germany in the midfield of the OECD scale of rigidities at the end of the 1990s. In particular, the strong presence of work councils hampers employees' mobility.[23] As a result, controlling for the presence of a work council at the establishment level, will be crucial for analyzing worker flows.

[21] A trend that has been identified by Card, Heining, and Kline 2013 as one of the main drivers of rising wage inequalities in West Germany in the early 2000s.

[22] Additional survey data on establishments' vocational training policies can be obtained from the IAB, but the response rate is too low to be used as a robust control.

[23] A works council is guaranteed by law in all plants with more than five employees. In plants with more than 20 employees the work council must agree to any layoff. Especially in larger establishments work councils often exist in combination with collective agreements.

1.3 Empirical strategy

My empirical strategy builds on the seminal work of ADH, and adapts it to the German context following DFS. I focus on the period 1997 to 2014. It comprises Eastern European countries' waves of entry in the European Union, as well as China's accession to the WTO in 2001, but excludes the actual fall of the Iron Curtain. I consider variables up to 1995 in order to construct pre-shock controls but not further.[24]

1.3.1 Trade exposure across local labor markets

I use the variation in initial industry specialization across local labor markets.[25] To measure a local labor market's exposure to changes in trade patterns, I consider the change in imports or exports over a given period of time, weighted by the initial industrial composition of the region. In particular, the import exposure can be written as:

$$TS_{it}^{M} = \sum_{j} \frac{E_{ijt}}{E_{jt}} \frac{\Delta Im_{jt}^{D \leftarrow East}}{E_{it}} \tag{1.1}$$

where i denotes the local labor market[26], j the industry, ΔIM_{jt} is the total change in imports (in thousands of 2005 euros) of industry j between t and $t+1$ from the "East" (China or Eastern Europe), E_{ijt}/E_{jt} represents region i's share of industry j in *manufacturing* employment at time t, and E_{it} is total manufacturing employment

[24] The German reunification was enforced on Oct. 3rd 1990. The inclusion of the "new" Federal States (East-Germany) in the German economy lead to substantial migrations of workers across regions and industries in response to institutional and political changes. As documented by Burda 1993 and Wolff 2009, approximately 1.7 million former residents of East Germany (about 10% of the population) moved to the West. An even larger inflow (roughly 2.8 million ethnic Germans) arrived from Russia and other former East bloc countries between 1988 and 2000. As such, 1995 is considered enough after the reunification to get rid of these institutional fluctuations (and ensure a clean set of data), but still capture the long-run opening of Germany to trade with Eastern Europe, as is made clear from Figure (1.2)

[25] For a description of the construction of the local labor markets, see Appendix A.

[26] In the paper, I use region or local labor market interchangeably. In specific instances, I use county level variation (*Kreis*) in which cases the distinction is emphasized.

in region i at t. This measure is thus capturing the change in import exposure of a German local labor market i given its initial sectoral employment as a proportion of the national change in sectoral imports.

I also consider regional export exposure with an analogous measure:

$$TS_{it}^{X} = \sum_{j} \frac{E_{ijt}}{E_{jt}} \frac{\Delta X_{jt}^{D \to East}}{E_{it}} \tag{1.2}$$

In total, I use the variation of a little more than 221 local labor markets (400 counties) across 119 three-digit level NACE rev. 1 industries.

The aim of the empirical analysis is to identify the causal effect of exposure to import competition from what DFS call "the East and the far East" on the local labor flows of German regions. In the baseline regression, I regress the change of a regional outcome variable Y_i between t and $t+1$ on the corresponding change in regional import and export exposure over the same time period:

$$\Delta Y_{it} = \beta_0 + \beta_1 \cdot TS_{it}^{M,East} + \beta_2 \cdot TS_{it}^{X,East} + X_{it}' \cdot \beta_3 + \gamma_{s(i)t} + \varepsilon_{it} \tag{1.3}$$

where i denotes a German local labor market, $TS_{it}^{h,East}$ denotes the exposure measures ($h \in \{M, X\}$), and X_{it} is a vector of controls that I discuss in detail below. The parameter $\gamma_{s(i)t}$ represents a set of federal state $\times$ year fixed-effects. To the extent that I am including East German local labor markets in my analysis, it seems important to control for the differential trend experienced by these states in particular in the early phases of my sample. Standard errors ε_{it} are clustered at the Federal state level. Adão, Morales, and Kolesár 2019 suggest that standard errors should instead account for correlation of the residuals across regions with similar sectoral composition. I use

their Stata routine in the specific case where I do not control for export exposure, and therefore only have a single shift-share variable in my specification.[27]

The empirical model presented in Equation (1.3) is similar to a difference-in-difference specification, insofar at it compares changes over time in employment in labor markets with differential treatments (namely import exposure to China or CEE). In this regard, such a regression can only identify relative (causal) effects but does not inform us on general equilibrium effects of increased trade with China or Eastern Europe that are common to all German labor markets.

As emphasized in the introduction, the choice of considering both import and export exposure measures within the same regression equation is motivated by both the balanced position of Germany with respect to China and CEE, and identification concerns. If there is a systematic positive correlation between import and export exposure, the import exposure measure will likely capture the effect of export exposure as well, generating an omitted variable bias. I confirm below that the high correlation between the two measures in the case of trade with Eastern Europe is a potential identification issue. In Appendix D I estimate regression 1.3 using only the import exposure measure. I find significantly different estimates with respect to trade exposure to Eastern Europe, confirming the need to control for the dynamic of exports when analyzing the causal effect of import exposure. The estimates with respect to trade exposure to China are however robust to considering import exposure alone.

[27] See Adão, Morales, Kolesár, and Zhang 2020a for a description of the algorithm. In practice, this requires to consider a separate variable for each industry×period pair to account for sectoral correlation at each period, and allow the residuals to impact the estimation of both the shift-share of imports, and of exports. Ideally, one would add a cluster (in practice a path between shifters) at the state level to account for autocorrelation of shifters across times, as suggested in Adão, Morales, and Kolesár 2019 in the section on applications with panel data. As emphasized in their paper, the newly inferred standard errors are often larger, and a lot of estimates lose significance in the context of German exposure with Eastern Europe, especially when the outcome variables are gross entry and exit flows. On the other hand, estimates of employment adjustments due to import competition from China often remain significant although at a larger confidence level.

I consider the effect of exposure from Eastern Europe and from China in two separate specifications. This allows me to compare employment adjustments in response to inter-industry trade to adjustments in response to intra-industry trade in intermediate inputs. I split my sample period in four: 1997-2001, 2001-2005, 2005-2010 and 2010-2014. The initial period corresponds to a "control" period, prior to China's accession to the WTO and to CEE's entry in the European union. 2001-2005 is the main period of interest with respect to trade opening with China — as it can be seen from Figure 1.1a that trade volumes with China experience a net acceleration from 2001 on —, whereas 2005-2010 is the key period to consider changes in trade patterns from CEE (again, Figure 1.2 characterizes 2005 as the year with the sharpest trade acceleration between Germany and CEE).[28]

The average 5-year regional exposure to import competition from Eastern Europe is €3,5655 per worker. Consistent with the patterns from Figure 1.2, the average measure of import exposure increases over time, and is €2,1809 higher in 2005-2010 than in 2001-2005. Export exposure, on the other hand, is on average €3,9416 per worker, and increases monotonically over time, with the largest increase occurring after 2005. Regional import exposure to China is on average €1,9408 per worker, and increases sharply between 2005 and 2010 (more so than between 2001 to 2005). Export exposure to China exhibits a similar pattern and increases from €830 in 1997-2001 to €3,360 in 2005-2010. Considering the correlation between the measures, I find that the correlation between import and export exposure measures from Eastern Europe is 0.62, whereas the correlation between import and export exposure from China is only 0.10. There is relatively weaker correlation between import exposure from the two regions: the correlation coefficient between my measures of import exposure from Eastern Europe and China is 0.09. There is substantial variation in these measures across German local labor markets (when considering both the standard deviation

[28]The length of the periods considered is not perfectly equal across years to avoid potential tendency breaks due to the Great Recession that hit Germany in 2009.

and the interquartile range, in Appendix B). The average measure of import exposure from Eastern Europe is almost equal in West and East Germany, whereas the average measure of import exposure from China is larger in East Germany. The average measure of export exposure from CEE is almost €400 higher in East than West Germany, a feature that can be explained by the proximity to the border, whereas the average export exposure to China is much larger in West Germany.

1.3.2 Instrumental variable strategy

The empirical model presented in Equation (1.3) may suffer from a number of endogeneity biases that I address in turn in this section.

First, I am essentially considering a treatment effect. As a result, the unit of analysis must be such that the treatment (namely the trade shock), has no impact on the "non-treated". Following the theoretical insights on commuting openness of local labor markets from Monte, Redding, and Rossi-Hansberg 2018, I use the institutionally defined local labor markets (*Arbeitsmarktregionen*) as my primary unit of analysis.[29]

Second, there are a number of institutional features presented in Section 1.2 that may affect both the local exposure to trade shocks, and local labor market elasticities, thereby generating an omitted variable bias. In particular, the vector X_{it} includes two sets of control (evaluated in 1995): the first one contains local labor market demographics (share of female and foreign workers, average education level in the region) and the second one the regional share of establishments belonging to a collective branch agreement, and the share of establishments possessing a work council. The former aims at ensuring that beyond the sectoral composition of the local labor market, the composition of the working population in a region (in particular the share of foreign workers that may have tie to the East, or the level of qualifications in the

[29] In Appendix D I repeat my analysis at the county level.

local workforce that may correlate with both the local trade exposure and specific labor supply elasticities) is accounted for. The latter is justified by the importance of work councils and regional wage agreements in shaping workers mobility and wage adjustments locally. Federal State $\times$ year fixed effects are included to account for further institutional trends that may generate similar omitted variable biases.

Third and finally, the main remaining endogeneity concern in Equation (1.3) pertains to the endogeneity of the trade exposure measures themselves. In particular, the main concern is the presence of unobserved demand and supply shocks that would simultaneously affect trade exposure and regional economic performance. I use an instrumental variable strategy that is close in spirit to the approach of ADH and identical to the strategy used by DFS. For each region i, I construct the following variables to instrument German regional trade exposure:

$$TS_{it}^{M,inst} = \sum_j \frac{E_{ijt-1}}{E_{jt-1}} \frac{\Delta Im_{jt}^{Inst \leftarrow East}}{E_{it-1}} \tag{1.4}$$

$$TS_{it}^{X,inst} = \sum_j \frac{E_{ijt-1}}{E_{jt-1}} \frac{\Delta X_{jt}^{Inst \rightarrow East}}{E_{it-1}} \tag{1.5}$$

where $\Delta Im_{jt}^{ADH \rightarrow East}$ (respectively $\Delta X_{jt}^{ADH \rightarrow East}$) measures changes in imports (respectively exports) of industry-j goods from (respectively to) the East for a group of countries that I denote "Inst" (for instrument). Finally, note that in these measures the sectoral weights used are evaluated at $t-1$. In practice this means that I use employment shares of sector j in local labor market i in 1995 (rather that at the beginning of the time difference represented by Δ) to weight imports and exports changes. This is done in order to address concerns of reverse causality if employment adjusted in anticipation of future trade exposure.[30]

[30] While it can be argued that the timing of China's entry in the WTO was a surprise for many members, it is harder to argue so in the context of the entry of Eastern European countries in the EU. To some extent however, the adaptation of Central and Eastern Countries to market economies in less than a decade may have come as a surprise for many businesses.

The idea behind the instruments defined in equations (1.4) and (1.5) is that the rise of Eastern Europe and China in global trade induces a supply shock for all countries trading with them, and not only Germany. Thus, focusing on these "Inst" countries allows me to capture essentially this supply shock, and to purge any other possible shock simultaneously affecting Germany's demand for trade and regional performance. Instrumenting both import and export exposure measures are key in addressing these concerns.[31]

The validity of these instruments hinges on three conditions: (i) the exclusion restriction must hold; (ii) the unobservable supply and demand shocks in the countries chosen as instrument group for the instruments in (1.4) and (1.5) should not be strongly correlated with those in Germany; and (iii) each instrument should have explanatory power.

For the exclusion restriction to hold, there should not be independent effects of trade flows with respect to the "Inst" countries used to construct (1.4) and (1.5) on German regional outcomes. Following DFS, I exclude direct neighbors of Germany, as well as members of the European Union and/or the Eurozone. The final countries considered are the following: Australia, Canada, Japan, New-Zealand, Norway, Singapore, South Korea and the UK. The particularly strong focus on developed Asian countries comes from the need to instrument German exports with respect to China, despite its unique position as a large exporter to China (only few countries in the world have in fact almost balanced trade with China as Germany).[32]

Relative to the second condition mentioned above, it is crucial that unobservable supply and demand shocks in the "Inst" group should not be strongly correlated

[31] *De facto*, only instrumenting import exposure and keeping export exposure as a standard control — which would have allowed me to compute standard errors with the routines from Adão, Morales, Kolesár, and Zhang 2020b; Adão, Morales, Kolesár, and Zhang 2020a — reintroduces the same endogeneity issues in the specification. In fact, the estimates obtained in this setting are close to the ones obtained when not controlling for export exposure.

[32] In Appendix D I consider an alternative group of countries as robustness check. The results are robust to considering all countries excluding the European Union and the US as instrumenting group.

Table 1.3: Instrumental variable strategy - First stage

	Eastern Europe			China		
	Coeff.	R-squared	F-test	Coeff.	R-squared	F-test
$TS_{it}^{M,inst}$	0.2226***	0.6295	5,279	0.0929***	0.1945	3,423
	(0.0355)			(0.0236)		
$TS_{it}^{X,inst}$	0.1729*	0.3526	458	0.0395**	0.3662	1,873
	(0.1336)			(0.0214)		

Note: This table reports the estimated coefficient, standard deviation, R^2 and F-statistic for a regression of the form:

$$TS_{it}^{h} = \alpha_0 + \alpha_1 TS_{it}^{h,inst} + +\alpha_2 TS_{it}^{-h} + X_{it}'\alpha_3 + u_{it}$$

where i denotes local labor market i, h denotes import (respectively export) exposure measure and associated instrument while $-h$ denotes the fact that the baseline specification is explicitly controlling for export (respectively import) exposure, and X_{it} includes the following controls: share of local manufacturing employment, share of female workforce, share of foreign workforce, share of routine workforce, share of establishments tied by a collective agreement, and state (*Bundesland*) $\times$ year fixed-effects. Standard errors are clustered at the Federal state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.011$

with those of Germany. When considering Western economies, a common critique arising with such an instrument is that the group of countries selected (usually other high-income countries) cannot purge the analysis from demand shocks that would be common across the Western economies. In the case of Germany, I argue that this critique is most likely less valid, at least at the beginning of the sample period. That is due to the particular position of Germany in the 1990s. Not only was Germany dealing with a big recomposition of its demand structure by incorporating East German states in West German economy, but West Germany itself was considered as the "Sick Man of Europe" (Dustmann et al. 2014). In clear contrast with other Western economies over the same period, it suffered from low growth and high unemployment rates.

Finally, Table (1.3) reproduces the first stage of the instrumental variable strategy for import and export exposure to Eastern Europe and to China separately.[33] Import exposure is systematically better instrumented than export exposure. Overall

[33]All the controls contained in X_{it} in Equation (1.3) are included.

however, the R-squared and F-statistics obtained for the first stage confirm that the instrumental strategy does not suffer from a weak instrument problem.

1.4 Results

In this section, I turn to my economic analysis of local occupational adjustments in response to a trade shock. I estimate Equation (1.3) using measures defined in (1.4) and (1.5) to instrument trade exposure defined in (1.1) and (1.2). In order to give context to my results, I first consider, in line with the literature, the causal effect of regional trade exposure on local manufacturing employment. I then turn to the main part of my analysis and focus on occupation-specific local labor market adjustments. In particular, I compare the local employment response to gross entry and exit flows from local establishments. This exercise is meant to compare net and gross employment adjustments for different types of occupational groups. Finally, I turn to the effect of trade exposure on the local labor demand. Again, this exercise is meant to compare gross labor adjustments to actual labor demand changes from local establishments.

1.4.1 Local labor market employment effects

Table 1.4 reports the estimates of the impact of local import exposure to CEE or China, when I do not control for regional export exposure. The estimates from an OLS regression are reported in columns (3) and (6). With an OLS specification, it appears that a €1,000 increase in regional exposure to import competition from China reduces manufacturing employment by 0.99 log points (significant at the 10% level). On the other hand, a €1,000 increase in exposure to import competition from CEE has a negative but insignificant effect on manufacturing employment. Amongst the demographic controls that affect changes in manufacturing employment, I find

that a higher initial share of routine workers has a negative impact on manufacturing employment, whereas a higher initial share of female workers on the other hand increases manufacturing employment. Interestingly, a 1 percentage point increase in the share of local establishment that have a work council will increase local manufacturing employment by 0.11 log points, whereas the share of establishment with collective agreements (at the branch level) has no significant impact. This is coherent with the notion of work councils working as a protection for insiders.

In columns (2) and (5), I instrument for the import exposure measures by using changes in imports from China or CEE from a group of countries with similar income level as Germany (excluding members of the European Union and the U.S.) described in Section 1.3, and cluster the standard errors at the federal state level. In the context of exposure to China (column (4)), I find that a €1,000 increase in import exposure decreases local manufacturing employment by a significant 7.4 log points. This suggests that there is an upward omitted variable bias in the OLS (positive demand shocks). In the context of import exposure with respect to Eastern Europe, the bias is similarly towards zero, as I now estimate that a €1,000 increase in import exposure decreases manufacturing employment by a weakly significant 0.13 log points. In columns (1) and (4), the standard errors are computed allowing for residuals to be correlated across regions with similar sectoral composition following the methodology of Adão, Morales, and Kolesár 2019. As expected, the standard errors are larger which makes it harder to reject the null hypothesis. The negative estimated effect of import competition from China remains nonetheless significant at the 5% level.

Overall, Table 1.4 confirms the substitution effect obtained in ADH: import competition from low-labor cost countries decreases local manufacturing employment. This effect is particularly strong for import competition from China, suggesting that the substitution effect is an order of magnitude larger in the context of inter-industry trade relative to intra-industry trade.

Table 1.4: Manufacturing employment effects of trade exposure

	Long-run change in manufacturing employment *percents - Mean = 2.24*					
	Eastern Europe			China		
	(1) (IV)	(2) (IV)	(3) (OLS)	(1) (IV)	(2) (IV)	(3) (OLS)
TS_{it}^{M}	-0.1259	-0.1259	-0.2000	-7.3957**	-7.3957***	-0.9924*
	(0.9000)	(0.0943)	(0.7800)	(3.8100)	(3.0805)	(0.5826)
% manuf. tradable goods		-0.5512**	-0.5546*		-0.6245**	-0.5599*
		(0.2985)	(0.3106)		(0.2826)	(0.3059)
% routine workers		-79.4274***	-79.6987**		-79.0334***	-79.3161**
		(29.8540)	(30.5761)		(32.4053)	(30.4907)
% female workers		87.4321**	87.4673**		99.3878**	89.2250**
		(39.6071)	(40.8065)		(46.4562)	(42.7684)
% foreign workers		-27.1637	-27.1463		-65.5069	-14.7938
		(94.0575)	(97.6274)		(77.5219)	(91.6686)
% collective agreements		0.0105	0.0107		0.0313	0.0130
		(0.0373)	(0.0387)		(0.0452)	(0.0397)
% est. w/ work council		0.1302***	0.1302***		0.1225***	0.1293***
		(0.0332)	(0.0346)		(0.0448)	(0.0355)
Time × State FE	✓	✓	✓	✓	✓	✓
Sectoral cluster	✓		✓	✓		✓
R^2	0.1087	0.1087	0.1071	0.0505	0.0505	0.1100
N	909	909	902	909	909	902

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in log manufacturing employment (in log points). Trade exposure is estimated separately for China and Eastern Europe. In columns (2) and (5) the estimated regression only clusters standard errors at the state level. As a result, only the main coefficient and its standard errors are reported (as all other controls are estimated the same). In column (1) and (4), standard errors are measured with the `ivreg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020a. Columns (3) and (6) report the full specification estimated with OLS and standard errors measured with the `reg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020b.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The concern with the specification described above is that it does not account for the ability of the local labor markets to also export to these newly opened partners. Yet, Germany has almost balanced trade with both China and Central and Eastern Europe, in particular in the later part of my sample. German firms export manufactured parts of motor vehicles, and machinery to both China and Eastern Europe. It is therefore likely that regional exposure to export opportunities will have a strong effect on local manufacturing employment. Table 1.5 therefore reports estimates of Equation (1.3) when the independent variables include both regional import and export exposure.

Columns (2) and (4) report again the OLS estimates. Interestingly, the coefficient for import exposure from China (column (4)) remains virtually unchanged compared to Table 1.4, whereas the coefficient for import exposure from CEE has changed sign, but remains insignificant. Instrumenting for both import and export exposure, one the other hand, changes the picture completely. A €1,000 increase in import competition from China is now estimated to decrease local manufacturing employment by a significant 6.5 log points, whereas a €1,000 increase in import competition from Eastern Europe *increases* local manufacturing employment by a significant 5 log points.

In essence, controlling for local export exposure has no impact on the estimates of import competition from China, and the coefficient from (instrumented) regional export exposure is insignificant. This makes intuitive sense when considering the composition of German trade with China: there is a very weak correlation between the two exposure measures, as Germany exports to China products that are not otherwise imported from there. As a result, there is no omitted variable bias in this context.

On the other hand, there is a very large correlation between imports and exports from and to Eastern Europe, as Germany's trade with CEE is characteristic

Table 1.5: Manufacturing employment effects of trade exposure

	Long-run change in manufacturing employment *log points - Mean = 2.24*			
	Eastern Europe		China	
	(1) (IV)	(2) (OLS)	(3) (IV)	(4) (OLS)
TS_{it}^{M}	5.01123**	0.1978	-6.4477***	-0.9930*
	(2.1597)	(1.0645)	(2.4427)	(0.5609)
TS_{it}^{X}	-16.9368**	-1.2281	-26.7993	-0.3221
	(7.1544)	(1.5716)	(21.4700)	(1.3868)
% manuf. tradable goods	-0.7794***	-0.5741*	-0.8077***	-0.5665*
	(0.1797)	(0.3055)	(0.2401)	(0.3007)
% routine workers	-94.7119***	-81.0299**	-104.0495**	-79.8938**
	(34.4906)	(31.0458)	(45.6600)	(31.5028)
% female workers	76.6617*	86.5441**	33.8170	88.4651**
	(44.0194)	(41.0231)	(68.4307)	(41.7503)
% foreign workers	45.9286	-21.2207	66.9269	-13.9545
	(106.0173)	(95.8652)	(96.7646)	(91.4120)
% collective agreements	0.0052	-0.0131	0.0417	0.0161
	(0.0397)	(0.0395)	(0.0507)	(0.0403)
% est. w/ work council	0.1357***	0.1305***	0.0936***	0.1288***
	(0.0308)	(0.0339)	(0.0327)	(0.0350)
Time × State FE	✓	✓	✓	✓
R^2	0.1224	0.1081	0.1552	0.1101
N	912	904	912	904

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the log of manufacturing employment (in log points). Trade exposure (both in terms of imports and exports) is estimated separately for China and Eastern Europe. In column (1) and (3), trade exposure measures are instrumented with a 2SLS estimator. Columns (2) and (4) report the full specification estimated with OLS. Skilled workers are defined as workers with a vocational or university degree. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of intra-industry trade. Furthermore, the detailed industries in which Germany is both importing and exporting with Eastern Europe are mainly industry codes relative to intermediate inputs. In this context of input-output linkages, the omitted variable bias becomes very clear. Conditional on a region being able to export a non-negligible part of local production to Eastern Europe, import exposure has in fact a

positive effect on local manufacturing employment. Conversely and perhaps surprisingly, conditional on a region importing a lot of the local industries' products from Eastern Europe has a strong and significant *negative* impact on local manufacturing employment (-17 log points). This is counterintuitive, as one usually expects export exposure to have positive employment effects due to local firms' expansion. In fact, this is what DFS estimate for German local labor markets over the period 1988 to 2008. This is not the case over the period 1997 to 2014, suggesting that the dynamic of trade between Germany and Eastern Europe has dramatically changed over the last decade of my sample.[34] Table 1.2 provides some possible explanations for these estimates: if one considers the automobile sector in particular, German imports for both motor vehicles and parts of have increased in similar proportions over the whole sample, whereas the composition of exports has changed in favor of parts of vehicles. It suggests that German trade with Eastern Europe is driven by vertical integration. In that regard, export exposure allows local labor markets to "export" (or offshore) manufacturing assembling labor to Eastern Europe, and import assembled parts that require additional labor to generate the finished products. This organization of production has been labeled as the "Bazaar economy" by Sinn 2006, who documents that German firms exploited massively the opening of Eastern Europe to relocate and offshore large chunks of the assembling parts of the value chain to its low labor-cost neighbors, before importing final products and applying the "made in Germany" label.

These qualitative patterns are robust to considering manufacturing employment shares rather than changes in levels (Table C1), and to allowing the definition of local labor markets to change: in Appendix D, I use narrower geographical units (counties) and re-estimate the effect of import exposure on local manufacturing employment.

[34] I estimated Equation (1.3) using local unemployment rate as the dependent variable, and found that export exposure to Eastern Europe does decrease local unemployment. My results are thus not excluding the expansion effect of export exposure, but suggest that the positive employment shift happened in non-manufacturing sectors.

Moreover, the estimates are also robust to changing the group of countries used in constructing the instruments and allowing for a larger range of them: the results can be found in Appendix D.

Overall, the presented results suggest that the effect of low-income countries import competition is not unilaterally detrimental to local employment. In particular, they show that the nature of the trade relationship is of importance, whether it is inter- or intra-industry trade. The labor substitution effect emphasized in the literature appears particularly clear in the specific context of import competition from China, a labor-intensive country. In the context of intra-industry trade of intermediate inputs however, it appears that import exposure is not necessarily import competition. In fact, conditional on a region being exposed to export opportunities within the same industries, import exposure has a positive effect on local employment. To test the hypothesis of the "Bazaar economy" further, and understand what type of activities are substituted or expanded in response to import exposure to Eastern Europe, I turn in the following section to an analysis of local employment adjustment at the occupation level.

1.4.2 Occupation-specific adjustments

I explore the change of regional employment of specific occupational groups in response to trade exposure. I focus in particular on the distinction between skilled and unskilled workers, and between white and blue collar workers. An analysis at a narrower level of occupation classification is available in Appendix C.

I use information on the occupational classification of workers derived by Blossfeld 1985 to construct broad occupational groups.[35] Blue collar workers include skilled and unskilled manual occupations, technicians and engineers. White collar occupations

[35]The existing three-digit occupational variables in the dataset are often too differentiated for the representation of socio-economic strata. Blossfeld's Occupational Classification was developed on the basis of the 1970 Census of Population and Occupation as a now commonly used alternative. See Table A1 in Appendix A for a description of this classification.

include unskilled and skilled services (both services to individual and administrative and commercial services), as well as management. The choice of these occupational groups is not *ad hoc*: it allows me to compare employment levels with the true variables of interest, namely the gross flows of workers in and out of German establishments, which are provided in terms of this classification in the data.[36]

Table 1.6 reports the estimated effect of import exposure on local employment shares of skilled and unskilled workers, differentiating blue and white collar workers. The variables considered here are net changes in the log of local employment, where trade exposure is instrumented as discussed in Section 1.3.[37] For each geographic region of exposure, I compare the estimated effect of import exposure on the employment of these occupations within manufacturing industries only with the local employment changes across all sectors.

Focusing first on exposure to trade with Eastern Europe (upper panel), I find that conditional on export exposure, import exposure has a positive effect on local employment across all occupations. The estimates are however only significant for Unskilled blue collars and Skilled white collars. In particular, I estimate that a €1,000 increase in the local import exposure measure, conditional on a given measure of local export exposure, increases the employment of unskilled production workers and technicians by manufacturing firms by 9 log points, and employment of skilled service workers by 6.93 log points. Amongst these occupations, Table C2 reveals that employment of skilled administrative and commercial workers and management workers by manufacturing firms increases the most. Conversely, conditional on import exposure, an increase in export exposure decreases significantly manufacturing employment of unskilled blue collar workers (and in majority non-technical occupations) and associated

[36] I exclude agricultural occupations, as well as semi-professions and professions that are overwhelmingly employed in the public sector that I don't observe in my data.

[37] Similar to the the analysis for aggregate manufacturing employment, I considered the effect of import exposure when the outcome variable is a difference in employment shares rather than the log ratio. The magnitudes obtained are naturally different, but the qualitative patterns are similar.

Table 1.6: Impact of trade exposure on occupation groups

	Dependent variable: change in local employment *log points*			
Mean Manuf. =	*2.23*	*-2.19*	*2.76*	*8.03*
(Mean All =)	*(-0.89)*	*(0.76)*	*(4.04)*	*(14.06)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	3.8756	9.3936***	6.9259***	4.9149
Manuf	(2.9252)	(3.4614)	(2.6147)	(3.7167)
TS_{it}^{X}	-10.6149	-34.6472***	-18.9737**	-13.9035
Manuf	(9.6590)	(11.5971)	(8.9962)	(12.3385)
TS_{it}^{M}	3.9297**	5.6706***	0.8346	0.5311
All	(1.7473)	(1.7708)	(1.4882)	(1.7944)
TS_{it}^{X}	-11.9808**	-21.0773***	-2.0175	-0.5430
All	(5.8640)	(5.9676)	(4.8712)	(5.9041)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	-2.3018	-9.2791	-2.9446	-4.2153*
Manuf	(2.8021)	(6.6394)	(2.5858)	(2.3678)
TS_{it}^{X}	-8.8894	-42.0752	-17.4982*	-6.2709
Manuf	(8.6068)	(34.1458)	(9.9802)	(8.1060)
TS_{it}^{M}	-1.1862	-4.5058	2.9369*	0.0292
All	(2.6089)	(4.1891)	(1.6254)	(1.1557)
TS_{it}^{X}	-22.3842**	-34.1887**	-14.0788***	-10.1355***
All	(10.3372)	(18.0960)	(5.7807)	(3.4389)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in occupation-specific log employment (the resulting outcome is a difference in log points). Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

skilled and unskilled clerical jobs (but much less management jobs). This is coherent with an organization of production, in which assembly line workers are offshored and employment of manual and in particular technical occupations (employment of

engineers is also significantly increased by import exposure) and administrative and commercial support occupations is increased.

Comparing these estimates with the effect of import competition on employment in the local labor market as a whole, one sees that the estimates are of the same sign but systematically lower, suggesting that the bulk of the effect of trade exposure is happening in manufacturing sectors.

Turning to exposure to trade with China (lower panel), I find the effect of import competition to be less significant when focusing on manufacturing employment than when considering occupation-specific local employment across all sectors. This suggests that trade exposure to China, and in particular export exposure conditional on import exposure, affects other sectors more than manufacturing industries in particular. Furthermore, an increase in export exposure to China has a significant negative effect on non-manufacturing employment of skilled manual workers and engineers, as well as clerical business services. These results are quite puzzling. A possible explanation is that export exposure to Chinese markets may encourage automation. This is however hard to reconcile with the fact few of the most negatively affected jobs are considered routine according to the classification of Blossfeld group from DFS, and that the effect would be stronger in the manufacturing firms if automation was driving the results. One conjecture I can make is that a large part of German exports to China involves mined products and raw metals, which are not classified as manufacturing *per se*. If these sectors are particularly underrepresented in my sample, it could drive the negative estimates across the board.

1.4.3 Dynamics of labor adjustment and labor demand

While the results in the previous section provide evidence of *net* local employment adjustment to trade exposure, I am ultimately after changes in establishments' demand for these specific occupation groups. I therefore turn in this section to an analysis of

gross flows. I focus in particular on gross entry and exit flows by occupation groups, and compare them with adjustment in the number of vacancies posted by individual firms.

Worker flows

Table 1.7 (respectively 1.8) reports the estimated adjustment of gross entry (respectively exit) flows by occupational groups to trade exposure.

Local exposure to trade with CEE has a significant effect on gross entry flows of manufacturing skilled workers, both blue and white collar (Table 1.7). Conditional on export exposure, import exposure favors entry of skilled business services (+5.9 percentage points) and decreases gross entry flows of skilled manual workers in particular.[38] Conversely, conditional on import exposure, export exposure to Eastern Europe has a significant positive effect on entry of skilled production workers (+5.1 percentage points) and decreases entry of skilled white collars. On the other hand, Table 1.8 reveals weak effects of trade exposure on gross exit flows (the majority of the coefficients are insignificant). This suggests that the positive employment effects of import exposure to Eastern Europe are driven by changes in local firms' hiring pattern rather than particularly strong layoffs or voluntary quits. In non-manufacturing sectors, the estimates suggests that import exposure encourages entry of low skilled manual workers, whereas export exposure has a significant large negative effect on this same group (-2 percentage points). These effects appear to be driven by gross flows of unskilled manual workers much more than technicians. This group would encompass warehousing or transport workers in particular, as well as packaging and repairing occupations, which may participate from the global value chain of a number of manufacturing sectors.

[38]The detail of the occupation-level effects are reported in Tables C3 and C4.

Table 1.7: Impact of trade exposure on entry flows

	Dependent variable: change in local entry rate *percentage points*			
Mean Manuf. =	*-0.64*	*-1.18*	*0.55*	*1.53*
(Mean All =)	*(-1.78)*	*(-1.32)*	*(-0.98)*	*(3.65)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	-1.6439***	-0.0322	0.5864**	0.4335
Manuf	(0.6625)	(0.6812)	(0.2868)	(0.5814)
TS_{it}^{X}	5.1234**	-0.5334	-2.1828**	-1.2637
Manuf	(2.2401)	(2.3243)	(0.9800)	(1.9393)
TS_{it}^{M}	-0.3019	0.5175**	-0.0737	-0.4005
All	(0.2913)	(0.2370)	(0.2079)	(0.4694)
TS_{it}^{X}	0.9235	-2.0237***	0.2366	1.3155
All	(0.9622)	(0.7834)	(0.6901)	(1.5392)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	0.0172	0.6747	-0.3817	0.1961
Manuf	(1.0216)	(1.2929)	(0.3400)	(0.4799)
TS_{it}^{X}	2.3810*	-1.6156*	-0.6056	1.7354
Manuf	(1.5423)	(1.0340)	(1.2111)	(2.5561)
TS_{it}^{M}	0.0760	-0.9224***	0.2637**	0.2635
All	(0.4054)	(0.2637)	(0.1440)	(0.3878)
TS_{it}^{X}	-0.1191	-1.1334	0.6899	2.1355
All	(1.1762)	(1.7112)	(0.9325)	(2.5746)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific entry rate (in percentage points). Entry rates are measured as the ratio of the total of workers entering a new establishment locally in a given year, in a specific occupation group, over the total number of entrant in a given year locally. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Considering trade exposure to China, it appears that import exposure has no significant effect on entry flows of manufacturing businesses, but a significant effect on entry in non-maufacturing sectors. In particular, I find that import exposure to

China increases entry of skilled white collar workers by 0.26 percentage points (in particular skilled service occupations that do not pertain to business services, such as pharmaceutical workers, safety testers, or judicial officers), and decrease entry of unskilled manual workers (-0.93 percentage points). However, export exposure to China encourages significantly entry of skilled production workers (+2.4 percentage points) and decreases gross entry of unskilled manual workers (-1.6 percentage points). Gross exit flows reveal that overall these manual workers, and in particular unskilled workers, experience larger turnover in response to exposure to Chinese trade.

The results presented above reveal changes in gross entry and exit flows' composition. An analysis in levels, rather than in shares, confirms these qualitative patterns. In particular, gross levels of entry are especially responsive to trade exposure to Eastern Europe, whereas gross levels of exit flows are particularly responsive to trade exposure to China. This distinction is interesting to the extent that it suggests a difference in firms' strategy for adjusting their workforce, whether by new hires or by retaining workers. Trade to Eastern Europe seems to generate a demand for new workers, in specific activities supporting the "Bazaar economy" (skilled clerical jobs and engineers), whereas trade with China seems to increase workers' turnover across all occupations, with no strong hiring patterns.

Vacancy posting and establishments' demand

Gross entry and exit flows provide insight on how the net employment effects are achieved through hires, layoffs and voluntary quits. But another facet of local labor markets response to trade exposure is the adjustment of the unemployment rate. While I do not have unemployment rates at the level of local labor markets, my data allows me to observe local firms' vacancy posting behavior. In models of trade with frictional unemployment (Davidson, Martin, and S. Matusz 1999, and for a comprehensive view, Davidson and S. J. Matusz 2010), not only does the labor market

Table 1.8: Impact of trade exposure on exit flows

	Dependent variable: change in local exit rate			
	percentage points			
Mean Manuf. =	*-0.12*	*-2.31*	*0.53*	*1.93*
(Mean All =)	*(-1.64)*	*(-1.63)*	*(-0.89)*	*(3.48)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	-0.8348	0.7071*	-0.0318	0.1063
Manuf	(0.7424)	(0.4915)	(0.3590)	(0.4251)
TS_{it}^{X}	3.2396	-2.7739*	-0.2790	-0.6594
Manuf	(2.4639)	(1.6236)	(1.2064)	(1.4073)
TS_{it}^{M}	-0.5157	0.2562	-0.0901	0.0722
All	(0.4816)	(0.1813)	(0.1968)	(0.4652)
TS_{it}^{X}	1.5375	-0.8519	-0.4632	0.0132
All	(1.5641)	(0.6139)	(0.6578)	(1.5311)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	-0.0604	0.0374	-0.0227	-0.1506
Manuf	(0.7588)	(0.6922)	(0.2749)	(0.3644)
TS_{it}^{X}	0.7397	-2.5574	0.8783	-0.4580
Manuf	(1.8050)	(2.3698)	(1.7338)	(0.6500)
TS_{it}^{M}	-0.1953	-0.4260***	0.1121	-0.0358
All	(0.2929)	(0.1268)	(0.2450)	(0.4040)
TS_{it}^{X}	-1.1192	-0.7331	0.8385	0.8620
All	(1.3014)	(1.2296)	(1.1539)	(0.6682)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific exit rate (in percentage points). Exit rates are measured as the ratio of the total of workers exiting an establishment locally in a given year, in a specific occupation group, over the total number of exiting in a given year locally. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tightness affect traded goods prices (Davidson and S. J. Matusz 2005), but also the adjustment of the factors of production are dependent on the ability of firms to fill their vacancy.

In this section, I estimate the causal effect of trade exposure on local vacancy posting. My working hypothesis here is that net employment effects may be driven by a mismatch between the demand for skills by firms, and the local supply of these. If trade exposure to a certain region increases firms' demand for specific occupations that are not met locally, net employment effects and gross flows are not going to reveal the full picture in terms of market adjustment.

Table 1.9 reports estimates of Equation (1.3) when the outcome variable is the five-year change in the number of vacancies posted locally by manufacturing establishments.[39] As in Section 1.4.1, I report the IV-specification and the OLS regression for each estimation, in order to illustrate the potential omitted variable biases addressed with the instrumental strategy.

Similar to what was noted for manufacturing employment, the OLS specification generates an omitted variable bias: it is clearly upward with respect to China, suggesting confounding effects of positive demand shocks, but downward biased with respect to Eastern Europe which would suggest that unobserved supply or demand shocks would in fact decrease the amount of vacancies posted locally.

Focusing directly on the estimates obtained by instrumenting both import and export exposure, I find patterns in line with the conjecture made above about entry and exit flows of workers. In particular, conditional on export exposure, a €1,000 increase in import exposure to Eastern Europe increases the number of vacancies posted by manufacturing firms by about 40 vacancies. Conversely, however, conditional on imports from Eastern Europe, manufacturing establishments decrease the vacancies they post in response to export exposure. This is coherent with an adjustment of the organization of production favoring offshoring of exporting regions and hiring of new workers in importing local labor markets.

[39] Because there is a non-negligible amount of zeros in terms of vacancies posted, I opted to consider changes in levels rather than changes in log.

Table 1.9: Trade exposure effects on vacancies posted

	Long-run change in regional vacancies posted *Number of vacancies - Mean = -47.96*			
	Eastern Europe		China	
	(1) (IV)	(2) (OLS)	(3) (IV)	(4) (OLS)
TS_{it}^{M}	40.1684**	1.1254	-14.1895***	-3.6040
	(20.4223)	(4.2061)	(5.9287)	(3.4125)
TS_{it}^{X}	-146.1054**	1.9639	15.4756	5.9171
	(69.7162)	(6.1498)	(44.5693)	(10.0367)
% manuf. tradable goods	-11.9595	-9.9183	-9.9915	-9.9705
	(8.9557)	(7.9592)	(7.7273)	(7.9686)
% routine workers	-55.6191	78.2766	86.5600	78.3056
	(146.5436)	(107.4935)	(124.2428)	(108.1396)
% female workers	398.3675	464.827*	514.5601**	479.9097*
	(324.4894)	(253.5304)	(265.7804)	(250.5847)
% foreign workers	-713.0714	-1389.702*	-1231.9080	-1347.165
	(1050.827)	(874.7654)	(885.7569)	(903.7129)
% collective agreements est.	-0.4538	-0.4249	-0.4041	-0.4168
	(0.3817)	(0.3544)	(0.3350)	(0.3564)
% est. w/ work council	-0.2771	-0.2713	-0.2414	-0.2626
	(0.3625)	(0.3081)	(0.2949	(0.3178)
Time × State FE	✓	✓	✓	✓
R^2	0.0628	0.1523	0.1778	0.1527
N	877	870	877	870

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the total number of vacancies posted locally. Trade exposure is estimated separately for China and Eastern Europe. In column (1) and (3), trade exposure measures are instrumented with a 2SLS estimator. Columns (2) and (4) report the full specification estimated with OLS. Skilled workers are defined as workers with a vocational or university degree. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

On the other hand, a €1,000 increase in local import exposure to China decreases the number of vacancies posted by about 14 vacancies. The effect of export exposure to China appears positive, as I find an estimated increase of 15 vacancies in response to a €1,000 increase in export exposure, but the coefficient is insignificantly different from zero.

Table 1.10: Impact of trade exposure on vacancy posting by occupation groups

	Dependent variable: change in local vacancy share *percentage points*			
Mean Manuf. =	*-18.65*	*-1.77*	*17.33*	*-2.23*
(Mean All =)	*(-14.34)*	*(2.83)*	*(10.88)*	*(-4.25)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	-2.4837	0.5487	-1.9785	5.8073
Manuf	(8.0113)	(4.5584)	(5.3643)	(6.6423)
TS_{it}^{X}	12.1046**	0.0141	-4.8701**	0.3929
Manuf	(6.0238)	(3.4736)	(2.6016)	(4.0100)
TS_{it}^{M}	-1.0466	1.5376**	-1.0035	5.5835**
All	(4.1979)	(0.7005)	(0.8746)	(2.8154)
TS_{it}^{X}	5.6842	-5.1594**	2.9948	-6.6575*
All	(4.1714)	(2.3080)	(2.8888)	(4.2251)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M}	-2.4747	1.1671	-1.4766	5.3337
Manuf	(2.6272)	(1.0249)	(1.3796)	(5.3302)
TS_{it}^{X}	17.8738***	9.3117	-13.2941*	12.45363
Manuf	(6.6481)	(10.1549)	(8.7975)	(14.3890)
TS_{it}^{M}	-0.7920	-1.7348***	2.5968***	-2.1958
All	(0.8163)	(0.7118)	(0.6927)	(1.7608)
TS_{it}^{X}	2.4742	-2.5620	-1.9535	1.0195
All	(3.1035)	(5.3630)	(4.6361)	(5.6973)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific vacancy share (in percentage points). Vacancy shares are measured as the ratio of the total number of vacancies posted by local establishments in a given year, for a specific occupation group, over the total number of vacancies posted in a given year locally. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To relate this increase in local firms' demand for workers to gross flows by occupation, and explore the hypothesis that trade exposure to Eastern Europe generates particularly strong hiring dynamics, Table 1.10 reports the estimate of Equation (1.3)

when the outcome variables are the share of each occupational group studied in Section 1.4.2 in the total of vacancies posted by firms in a given local labor market. As in the previous sections, I compare composition changes in vacancies posted by manufacturing firms to overall local changes.

In the context of trade with Eastern Europe, the gross flow patterns of entry of skilled blue collars and skilled white collars are matched by changes in the composition of vacancies posted by manufacturing firms. In particular, export exposure to CEE conditional on import exposure is associated with a significant increase in vacancies posted for production workers (+12.1 percentage points), and a reduction in the share of vacancies posted for skilled white collar workers. As the coefficients associated with import exposure are however all insignificantly different from zero, I cannot clearly explain, at this level of occupational detail, what is driving the increase in vacancies posted by manufacturing establishment in response to imports from CEE.[40]

The change in demand for workers in non-manufacturing firms is one aspect of trade not evaluated in Table 1.9. In this regard, the estimates suggest that conditional on import exposure, export exposure to Eastern Europe decreases the share of vacancies posted for unskilled workers, and more so than the increase in these same shares generated by import exposure.

In the context of import competition from China, the insignificant estimates of vacancy share changes in response to import exposure do not allow me to explain clearly the estimated decrease in vacancy posting from Table 1.9. It is however clear that the increase in vacancies posted in response to export exposure might be driven by the increase in the share of vacancies for skilled production workers from manufacturing firms. The lower panel of the table also suggests that import exposure

[40]Unfortunately the vacancies data are not available at the level of Blossfeld occupation groups. It might be the case that within categories of white and blue collars, vacancies posted in favor of one occupation counteract the change in vacancies posted for another occupation, leading to null aggregate effects.

also affects the vacancy posting behavior of non-manufacturing businesses in favor of skilled white collar jobs and away from unskilled manual occupations.

Overall the analysis of the dynamic adjustment of local labor markets' employment to regional trade exposure suggests that the differential net effects observed in the context of inter- versus intra-industry trade are also driven by differential entry and exit flows locally. In particular, intra-industry trade in intermediate inputs seems to favor an adjustment of the workforce through increased entries and hires (as well as vacancies posted), whereas inter-industry trade generates increased hiring in the context of export exposure, and overall increased turnover in the context of import exposure.

To conclude this analysis, I return to the initial conjecture that the counterintuitive effects on local employment associated with trade exposure to Eastern Europe can be explained by an organization of production in which assembly and non-technical manufacture are offshored to focus onshore employment on the manufacture of final products. The results obtained in terms of dynamic flows in and out of local establishments tend to confirm the story proposed. In particular, export exposure favors hires of skilled manual occupations, while import exposure favors hires of skilled business service occupations in manufacturing sectors. The overall adjustment of the number of vacancies posted by manufacturing establishments also favors the hypothesis of a strong offshoring component of exports to Eastern Europe. The more detailed analysis of vacancy composition, however, does not add much additional insight.

1.5 Conclusion

In this paper, I estimate the causal impact of import competition from low-income countries on local labor markets' employment. I distinguish between exposure to import competition in the context of inter-industry trade and of intra-industry trade

in intermediate inputs by focusing of the adjustment of German labor markets to trade with both China and Central and Eastern Europe.

I find that in the context of intra-industry trade with input-output linkages, import exposure is not necessarily associated with import competition. Crucially, controlling for a local labor market capacity to export products in the same industries as the ones exposed to import exposure reveals that import exposure has positive local employment effect. In the specific context of Germany's trade with Eastern Europe, I find strong evidence of what has been labeled as the "Bazaar economy" hypothesis. Vertical integration of German importers and exporters with their Eastern European partners generates an incentive to export raw products and offshore low-skilled assembly labor, leading to a strong negative employment effect of export exposure, conditional on local import exposure. On the other hand, conditional on exporting these initial parts of the value chain, an increase in exposure to imports of assembled and semi-finished products generates positive employment effects, in particular in low-skilled production jobs and skilled business services used in the downstream stages of the production chain. This adjustment of employment occurs dynamically through increased entry and hires of these particular occupations.

My results on import exposure from China, on the other hand, confirm the labor substitution effects emphasized in the context of inter-industry trade. In particular, import competition from China reduces manufacturing employment, increases gross exit flows and turnover, and decreases vacancy posting.

The differences emphasized between inter- and intra-industry trade raise some interesting questions for future research. In modern trade relationships, intra-industry trade in particular is characterized by global value chains, where even within a narrowly defined industry codes traded merchandises can differ in their position along that value chain. Accounting for upstreamness and downstreamness of imported and exported materials within narrowly defined industries may modify the notion of im-

port competition the way it is measured in this paper, and explain better the observed employment adjustment patterns. Promising avenues in that respect can be found in the work of Hausmann and Hidalgo 2011; Hausmann and Hidalgo 2010 and their measure of an input "ubiquity", or more recently in the work of Ferrari 2020, which develops an index of upstreamness that can readily be adapted to a number of industry classification codes. Another potential avenue of research could be explored in the divergence between entry and exit flows in response to import competition. The LIAB dataset contains separate modules documenting not only vacancy posting from German establishments, but also the specific types of layoffs composing gross exit flows (e.g. distinguishing between voluntary quits and layoffs for economic reasons). Pairing the two variables with information on local labor market tightness using local measures of unemployment rates would allow one to measure unemployment mismatch, as formally theorized for the U.S. by Şahin et al. 2014. This could deepen our understanding of the impact of import competition on general skills' obsolescence.

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Appendices

A Data Appendix

Trade data

The original data is extracted from the BACI database provided by the CEPII, publicly available for researchers already subscribing to the United Nations COMTRADE database. BACI provides bilateral values and quantities of exports at the HS 6-digit product disaggregation (5018 products classified according to the 1992 classification), for more than 200 countries since 1995. The data contains approximately 7.3 million yearly observations (with important variation across years). The initial yearly datasets are merged into a panel between 1995 and 2014.

I isolate 4 countries/group of countries of interest:

- Germany
- China
- Eastern Europe (EE) - 15 countries:
  Belarus, Bulgaria, Czech Republic, Estonia, Georgia, Hungary, Latvia, Lithuania, Moldova, Poland, Romania, Russian Federation, Slovakia, Slovenia, Ukraine
- "Inst" countries
  In the baseline estimation, this aggregate represents only 9 countries: Australia, Canada, Israel, Japan, New Zealand, Norway, Singapore, South Korea, UK.
  To address the weak instrument with respect to export exposure from China, I also consider a version of this aggregate with all countries available, excluding the United States of America and EU members.

For each year and each given product, the bilateral flows of these for groups are aggregated (for the EE and Inst groups). Only these observations are kept in the panel dataset. The final dataset is a panel that contains 18,536 observations and includes both imports and exports between country pairs.

As the variable for the value of the trade flows is denoted in current dollars, I convert these in euros using exchange rate times series publicly available:

- From 1995 to 1998: I use the ECU/USD conversion rate provided by the Saint Louis FRED
- From 1999 to 2015: I use the yearly EUR/USD exchange rate publicly provided by the Bundesbank

In order to convert the nominal value of bilateral trade flows into 2005 euros values, I correct for the Harmonized Consumer Price Index variation, using publicly available time series from Eurostat.

Crosswalk construction

To my knowledge, there is no publicly available correspondence between 1992-HS product classification codes and NACE rev.1 3-digit industry codes (which corresponds to the 3-digit level German classification of economic activities WZ93_3).
I constructed a mechanical crosswalk using publicly available correspondence tables:

- between the 1992-HS classification and ISIC rev. 3 (International Standard Industrial Classification of All Economic Activities, Rev.3)
- between ISIC rev. 3 and NACE rev. 1

The mechanical match is performed on Matlab. It associates every HS product code to its ISIC code(s), and then match it to the NACE industry code(s), creating as many duplicates as necessary for ambiguous cases. There are 76 HS product codes

that are not matched to an ISIC industry code in the correspondence table. For the time being, I created an additional category (ISIC 99.99/ NACE 9999). The correspondence table for ISIC-NACE are provided at the 4-digit level. The German classification of economic activities of 1993 matches the NACE rev. 1 classification up to 4-digits. In order to remove as many ambiguous cases as possible, I then aggregate at the 3-digit level. It leaves the crosswalk for 5018 product codes with 4166 unique matches, 1248 cases where one HS code is associated to two NACE codes, and 684 HS cases where one HS code is associated to three NACE codes. Ambiguous cases are weighted in equal proportions, by lack of better data available. I use this crosswalk with the constructed weights to aggregate product level trade flows at the 3-digit industry level. The final dataset contains 18,536 observations, with approximately 930 yearly observations.

Geographical unit of analysis - Local labor markets

The German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) publicly provides a geographical divide of the German territory in local labor market regions (*Arbeitsmarktregionen*). The classification has been initiated by the Federal Ministry for Economic Affairs and Energy (BMWI - and most recently by Karlsruhe University) to improve the regional economic structures. The labor market regions are not delimited annually, but once for a period of four to six years. In principle the identified labor market are defined as circular encompassing one or several counties (*Kreisen*), with the exception of the Berlin area in 1990, 1996 and 2000. The German Federal Institute for Research on Building, Urban Affairs and Spatial Development kindly provided me with a crosswalk between German counties and local labor markets for the years 1990, 1996, 2000, 2005 and 2011.

The German structure of the counties is not constant across time, neither is the geographical divide into local labor markets. There exist 468 *Kreisen* in 1995 and

402 *Kreisen* in 2011, whereas there are 265 *Arbeitsmarktregionen* in 1995 and 247 in 2011. In order to maintain some time consistency in the analysis, I select a balanced panel of 221 *Arbeitsmarktregionen* that exist throughout the sample period.

Occupational classification definition

Table A1 defines the coarse occupational classification of German jobs according to Blossfeld 1985. Three-digit occupations codes are classified by typical educational level of workers, average earnings, and types of activities performed at the job. They are designed to represent socio-economic strata of the German employed population.

Table A1: Coarse Occupational Classification (Blossfeld)

Coarse occupational category	Wage	Examples
Production		
Unskilled manual occupations (UMO)	68.55	Assembly, conveyors, and riveter workers, roadmaker
Skilled manual occupations (SMO)	84.81	Electricians, mechanics, carpenters, lab assistant, vehicle repairers, carpenters
Technicians (TEC)	151.02	Mechanical engineer, surveying technicians
Engineers (ENG)	279.74	Architect, (electro-, ...)engineers, chemists
Service		
Unskilled service occupations (USO)	58.67	Janitors, waiters, receptionists, conductors, warehouse managers, packers, cleaners
Skilled service occupations (SSO)	93.32	Train drivers, hairdressers, pharmacy chemists, judicial officers, administr. and enforcers, medical receptionists, pharmaceutical assistants, property managers, safety testers
Semi-professions (SEMI)	127.77	Nurses, social workers, teachers, journalists, translators, archivists
Professions (PROF)	223.31	Doctors, (economic and social) scientists, professors, legal consultants, statisticians
Administration		
Unskilled commercial and admin. (UCA)	73.95	Cashiers, auxiliary office (secretaries), auxiliary commercial agents (buyer, seller)
Skilled commercial and admin. (SCA)	131.91	Bankers, accountants; forwarding, logistics specialists; wholesale traders, data processing, office specialists
Managers (MAN)	277.71	CEOs, business owners, high-level public servants

Note: This table describes the broad occupational classification by Blossfeld 1985. Each group represents a socio-economic strata of the German workforce by similar education levels, average earnings, as well as types of activities performed. Daily wages are drawn from a cross section in 2010.

Summary statistics - German establishments and workforce

The German industrial fabric is characterized by what has been called the *Mittelstand*, that is a collection of small and medium-size establishments highly specialized and encouraged by a training system favoring the development of a skilled production workforce. Table A2 shows that the average size of a German establishment is around 20 workers, with a share of skilled workers above 50%.[41] Note that we include both blue and white collar skilled workers in this category, which explains that only 25% of the workforce is classified as white collar worker (where we include both skilled and unskilled workers).[42] This suggests a large proportion of skilled blue collar workers, a feature that has often been mentioned as a reason for Germany's industrial resilience. More than 75% of the establishments are identified as single-establishment firms. A large share of German establishments follows an industry-wide collective wage agreement (37%, with a declining share over the sample period). The sample of establishments is supposed to be representative of East Germany from 1996 on, and for Germany as a whole from 2001 on. Over the period 2001-2014, the average share of establishments located in West Germany is around 70%.[43,44]

One of the main explanations offered to explain the resilience of the German economy in the 2000s is Germany's important trade integration. As a matter of fact, almost 25% of German establishments are importers, but only 9% of German estab-

[41] In the LIAB dataset, skilled workers are identified as workers with a vocational training or university degree. The share of the German population with a vocational training averages around 30%.

[42] White collar workers are defined as workers whose 3-digit occupation code belong to one of the following one-digit categories: "Qualified service workers" and "Unqualified service workers", which target occupations from the service sector, and therefore exclude clerical business services that can be found in both the manufacturing and the service sector.

[43] East-German establishments are on average smaller, more often single-establishment, and less likely to be both exporter or importer than West-German establishments.

[44] I verify the dispersion of broad industries in East and West Germany. Even though all industries are more present in the West, manufacturing industries are relatively more evenly allocated, whereas services are massively allocated to West Germany. Interestingly, if one looks at the distribution of trade-exposed industries, East Germany is more exposed to tradable industries than West Germany (because of this unbalance in services).

lishments can be considered as exporters.[45] In terms of industries, 19% of German establishments belong to an industry that is exposed to international trade (that is an industry that appears in the trade data). However, the share of manufacturing establishments is fairly small (10% on average, with a decline of 2 percentage points over the sample window).

Despite a large peak in unemployment around the 2001 recession, turnover in German establishments, defined as the difference between the entry and exit rates of workers, remains fairly stable over the sample period, around 41%.[46] The vacancy rate averages at 3% over the period 1995-2014. Among the vacancies posted by German establishments, the share of vacancies devoted to skilled occupations remains fairly stable over the whole sample period, at the very high rate of 82% on average. On the other hand, the share of vacancies posted for white collar occupations (recall that this encompasses both skilled and unskilled white collar occupations) increases sharply in the mid-2000s (around the entry of Eastern European countries in the European Union), with a jump from 60% in 2005 to 81% in 2006.

[45] These numbers are very large. As a comparison point, Bernard, Bradford, et al. 2007 document that 4% of U.S firms can be identified as exporters in 2000.

[46] Alda, Bellmann, and Gartner 2005 associate the trend in the rise of entry and exit rates over the period 1993-2000 with a flexibilization of German labor markets.

Table A2: Summary statistics - Sample of establishments

	Mean	Std. dev.	N (millions)
Size (# employees)	23.53	302.74	36.7
Share of manufacturing est.	0.10	0.30	36.7
Share of exporters	0.09	0.29	17.0
Share of importers	0.24	0.42	4.9
Share of West-German est.	0.79	0.41	36.7
Share of single-est. firms	0.77	0.42	36.7
Share of est. w/ collective wage	0.37	0.48	36.7
Share of est. w/ work council			36.7
Workforce composition			
Share of skilled workers	0.55	0.30	36.6
Share of white collar workers	0.26	0.33	36.6
Share of female workers	0.48	0.33	36.6
Share of foreign workers	0.22	0.21	8.4
Average daily wage	66.66	38.14	31.2
Workforce flows			
Vacancy rate	0.03	0.13	34.6
Entry rate	0.41	0.57	21.9
Exit rate	0.42	0.93	21.1

Note: This table reports summary statistics for the sample of establishments from the LIAB. Observations are weighted by cross-sectional weight in order to make the sample representative of the German economy. Tradable industries are identified as 3-digit codes appearing at least once in the sample of bilateral trade flows. Skilled workers are workers with a vocational training or a university degree. White collar workers are workers with occupation codes belonging to the coarse 1-digit categories of "Service occupations" (skilled and unskilled). Entry and exit rates of workers are provided at the establishment level in the LIAB data. Finally, vacancy rates are measured as the ratio of total vacancies posted to the Social Security administration in a given year over total number of employees.

B Trade exposure - Summary statistics

Table B1: Trade exposure shocks - Description

	Eastern Europe			China		
	Mean	Std. dev.	IQR	Mean	Std. dev.	IQR
$TS_{it}^{M,97-01}$	2.9116	2.1415	2.3049	1.1110	2.2394	0.5941
$TS_{it}^{M,01-05}$	1.6597	1.1633	1.1317	1.6499	2.1284	1.3380
$TS_{it}^{M,05-10}$	3.8407	2.6582	2.2788	4.3550	5.3733	3.1927
$TS_{it}^{M,10-12}$	5.7980	7.7768	3.4134	0.6183	6.3683	2.0031
$TS_{it}^{X,97-01}$	2.8384	2.0532	1.9519	0.8307	0.6791	0.6788
$TS_{it}^{X,01-05}$	3.1120	1.4370	1.6970	0.9547	0.7597	0.8802
$TS_{it}^{X,05-10}$	4.4574	2.2170	2.4143	3.3591	2.3119	2.5976
$TS_{it}^{X,10-12}$	5.2802	3.5981	3.1691	2.6676	2.0948	2.5923

Note: This table reports summary statistics on the import and export exposure measures defined in Equation (1.1) and (1.2) for China and Eastern Europe separately. Units are thousand of 2005 euros per worker.

Table B2: Correlation of regional import and export exposure measures

	$TS_{it}^{M,EE}$	$TS_{it}^{X,EE}$	$TS_{it}^{M,C}$	$TS_{it}^{X,C}$
$TS_{it}^{M,EE}$	1.0000			
$TS_{it}^{X,EE}$	0.6183	1.0000		
$TS_{it}^{M,C}$	0.0953	0.1312	1.0000	
$TS_{it}^{X,C}$	0.2504	0.3938	0.1012	1.0000

Note: This table reports the pairwise correlation between each (10-year) exposure measure defined in Equation (1.1) and (1.2) across regions. Index EE stands for exposure to trade with Eastern Europe and C for exposure to trade with China.

C Additional margins of adjustment

Table C1: Manufacturing employment effects of trade exposure

	Long-run change in manufacturing employment share *percentage points - Mean = -0.70*			
	Eastern Europe		China	
	(1) (IV)	(2) (OLS)	(1) (IV)	(2) (OLS)
TS_{it}^{M}	0.9254	-0.0456	-1.4315***	-0.1423
	(0.5958)	(0.1400)	(0.2683)	(0.1106)
TS_{it}^{X}	-3.3413*	-0.1469	-2.5811	0.1004
	(1.9758)	(0.2803)	(2.5244)	(0.2693)
% manuf. tradable goods	-0.2348***	-0.1932***	-0.2266***	-0.1901***
	(0.0623)	(0.0225)	(0.0436)	(0.0211)
% routine workers	-17.7744***	-13.9978***	-15.8075***	-13.4616***
	(3.3556)	(2.9081)	(3.4750)	(2.8569)
% female workers	17.1014***	20.2268***	15.9352*	20.9466***
	(6.3648	(7.4301)	(9.5374)	(7.6655)
% foreign workers	-20.9425*	-37.0924**	-15.5814	-36.0523**
	(11.6109)	(16.2408)	(27.7356)	(15.8376)
% collective agreements	0.0203**	0.0220**	0.0271***	0.0222**
	(0.0090)	(0.0100)	(0.0089)	(0.0100)
% est. w/ work council	0.0306***	0.0283***	0.0246***	0.0282***
	(0.0124)	(0.0088)	(0.0085)	(0.0086)
Time × State FE	✓	✓	✓	✓
R^2	0.0947	0.0947	0.2172	0.0957
N	939	932	939	932

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 10-year change in the share of manufacturing employment (in percentage points). Trade exposure (both in terms of imports and exports) is estimated separately for China and Eastern Europe. In columns (1) and (4) the estimated regression only includes the regional employment share in tradable goods industries in the set of controls X_{it}. In column (2) and (5) the full set of controls is included. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Columns (3) and (6) report the full specification estimated with OLS. Skilled workers are defined as workers with a vocational or university degree. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C2: Impact of trade exposure on local employment of occupation groups

	Dependent variable: change in local employment								
	log points								
Mean Manuf. =	*-3.49*	*0.79*	*4.03*	*9.38*	*9.18*	*2.52*	*1.89*	*0.53*	*8.92*
(Mean All =)	*(0.41)*	*(-2.79)*	*(1.66)*	*(10.34)*	*(17.47)*	*(11.49)*	*(9.40)*	*(3.01)*	*(14.33)*
Exposure to Eastern Europe									
	UMO	SMO	TEC	ENG	USO	SSO	UCA	SCA	MAN
TS_{it}^{M}	9.8472**	3.2235	8.3073**	12.8044*	-1.3287**	-0.9620	11.7610***	6.5370***	1.6982**
Manuf	(4.5156)	(2.6825)	(4.0720)	(7.2228)	(0.5989)	(3.7878)	(5.4684)	(2.3822)	(0.7154)
TS_{it}^{X}	-37.9685***	-8.5515	-23.7158*	-40.3897*	2.3858*	5.0732	-36.2890**	-17.3322**	-3.5307*
Manuf	(15.0634)	(8.8066)	(13.8383)	(23.8199)	(1.3303)	(11.7728)	(18.3476)	(8.1657)	(1.7536)
TS_{it}^{M}	6.6585***	3.6149***	2.4081	7.0353	-1.2661	-1.6984	4.5286***	1.9370	2.9335
All	(2.0613)	(1.4975)	(2.4395)	(4.8390)	(2.4343)	(2.2444)	(1.5133)	(1.5365)	(2.5852)
TS_{it}^{X}	-25.2951***	-10.9652**	-6.4046	-22.3111	5.6818	6.4399	-14.7425***	-5.3686	-12.6914
All	(6.6609)	(4.9779)	(8.1131)	(15.9686)	(8.1912)	(7.1646)	(4.8592)	(5.0009)	(8.3065)
Exposure to China									
	UMO	SMO	TEC	ENG	USO	SSO	UCA	SCA	MAN
TS_{it}^{M}	-10.2865	-1.4182	-3.4311	-6.4756**	-2.6815	0.2883	-8.0518**	-2.9276	1.4342
Manuf	(8.1713)	(3.9831)	(3.1965)	(2.9131)	(2.2298)	(2.0694)	(3.9768)	(2.3881)	(6.7990)
TS_{it}^{X}	-45.8660	-12.3038	-11.5480	1.4304	5.8951	-9.2210	-30.7525*	-18.4360	7.1351
Manuf	(37.0051)	(9.2324)	(11.7154)	(9.4248)	(13.0500)	(20.0459)	(17.3950)	(11.7320)	(30.4592)
TS_{it}^{M}	-6.1825	-1.1035	2.5217	-0.2120	2.4557*	5.3644	-4.2131**	2.3296*	-1.7339
All	(4.1927)	(3.5660)	(3.4162)	(3.0239)	(1.4775)	(4.1585)	(1.8277)	(1.2950)	(2.4102)
TS_{it}^{X}	-42.6305*	-24.3955**	-4.8047	-14.9813**	-4.6633	1.2420	-29.8875**	-15.4913***	-17.6007*
All	(23.4670)	(11.4557)	(12.3478)	(7.0324)	(3.3393)	(11.2384)	(13.9241)	(4.5404)	(9.3407)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific log employment. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Impact of trade exposure on local composition of entries by occupation groups

	Dependent variable: change in entry rates *percentage points*								
Mean Manuf. =	*-1.36*	*-0.72*	*0.18*	*0.08*	*1.32*	*0.12*	*0.23*	*0.37*	*0.12*
(Mean All =)	*(-1.04)*	*(-1.68)*	*(-0.29)*	*(-0.10)*	*(2.55)*	*(-0.29)*	*(1.10)*	*(-0.67)*	*(-0.03)*
Exposure to Eastern Europe									
	UMO	SMO	TEC	ENG	USO	SSO	UCA	SCA	MAN
TS_{it}^{M}	-0.0229	-1.8025***	-0.0299	0.1756	-0.4045	0.1482	0.8521**	0.5912**	-0.0603
Manuf	(0.6897)	(0.7525)	(0.1932)	(0.1751)	(0.3590)	(0.4935)	(0.4600)	(0.3047)	(0.0889)
TS_{it}^{X}	-0.3266	5.7898**	-0.1373	-0.7224	1.4664	-0.5829	-2.8047*	-2.0372**	0.0853
Manuf	(2.3543)	(2.5476)	(0.6441)	(0.5860)	(1.1441)	(0.8420)	(1.6089)	(1.0373)	(0.2936)
TS_{it}^{M}	0.5241**	-0.3449	-0.0071	0.0480	-0.7773**	-0.1168	0.3835*	0.0296	-0.0037
All	(0.2474)	(0.2854)	(0.0433)	(0.0391)	(0.3437)	(0.1423)	(0.2390)	(0.2812)	(0.0827)
TS_{it}^{X}	-2.0613***	1.1040	0.0397	-0.1975	2.5918**	0.4594	-1.2975*	0.1441	-0.0223
All	(0.8185)	(0.9466)	(0.1274)	(0.1346)	(1.1351)	(0.4602)	(0.7805)	(0.9274)	(0.2665)
Exposure to China									
	UMO	SMO	TEC	ENG	USO	SSO	UCA	SCA	MAN
TS_{it}^{M}	0.4194	0.2432	0.2741*	-0.2503*	0.5115*	-0.1509	-0.2948	-0.2628	-0.0485
Manuf	(1.2016)	(0.9710)	(0.1584)	(0.1520)	(0.3139)	(0.1517)	(0.2255)	(0.3152)	(0.0611)
TS_{it}^{X}	-2.4756**	2.8754**	0.8138	-0.5609**	1.9346	-0.5905	-0.1668	0.1530	-0.6157
Manuf	(1.2881)	(1.5072)	(1.2181)	(0.2610)	(2.6300)	(0.6068)	(0.7177)	(1.2305)	(0.5013)
TS_{it}^{M}	-0.9730***	0.0950	0.0522	-0.0251	0.9001***	0.3635*	-0.6384***	0.1946**	-0.2944*
All	(0.2546)	(0.3861)	(0.0429)	(0.0197)	(0.3760)	(0.2366)	(0.2204)	(0.0982)	(0.1643)
TS_{it}^{X}	-1.5288	0.0851	0.4055	-0.2255	2.7906	-0.1532	-0.6628	0.7567	0.0754
All	(1.9532)	(1.1745)	(0.3080)	(0.1452)	(2.8088)	(0.6036)	(1.2819)	(0.6888)	(0.4197)

This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific entry rate (in percentage points). Entry rates are measured as the ratio of the total of workers entering a new establishment locally in a given year, in a specific occupation group, over the total number of entrants in a given year locally. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C4: Impact of trade exposure on local composition of exits by occupation groups

	Dependent variable: change in local exit rates *percentage points*								
Mean Manuf. =	*-2.31*	*-0.29*	*-0.001*	*0.18*	*1.46*	*-0.07*	*0.51*	*0.33*	*0.26*
(Mean All =)	*(-1.48)*	*(-1.65)*	*(-0.14)*	*(0.01)*	*(2.63)*	*(-0.33)*	*(0.87)*	*(-0.48)*	*(-0.09)*
Exposure to Eastern Europe									
	UMO	SMO	TEC	ENG	USO	SSO	UCA	SCA	MAN
TS_{it}^{M}	0.5531	-1.0288	0.1689	0.2352	-0.0223	-0.0253	0.1051	0.4104	-0.4476***
Manuf	(0.3889)	(0.7757)	(0.3307)	(0.1983)	(0.3452)	(0.0743)	(0.2584)	(0.4069)	(0.01851)
TS_{it}^{X}	-2.2432*	4.0129	-0.5733	-0.9094	0.0771	0.0645	-0.7146	-1.5834	1.3071**
Manuf	(1.2721)	(2.5886)	(1.0828)	(0.6625)	(1.1355)	(0.2420)	(0.8798)	(1.3693)	(0.6181)
TS_{it}^{M}	0.2040	-0.6468	0.0518	0.1429	-0.2784	-0.0792	0.3378	0.1883	-0.0204
All	(0.1667)	(0.4545)	(0.1721)	(0.0965)	(0.2932)	(0.1035)	(0.5320)	(0.1432)	(0.1120)
TS_{it}^{X}	-0.8069	1.9951	-0.0435	-0.4968	1.1865	0.3998	-1.1359	-0.8528*	-0.0043
All	(0.5493)	(1.4763)	(0.5808)	(0.3287)	(0.9573)	(0.3340)	(1.7512)	(0.4933)	(0.3620)
Exposure to China									
	UMO	SMO	TEC	ENG	USO	SSO	UCA	SCA	MAN
TS_{it}^{M}	-0.4141	0.3253	0.4743*	-0.4079***	0.4284*	-0.1506	-0.5671***	-0.0520	0.0065
Manuf	(0.5101)	(0.6968)	(0.2907)	(0.0720)	(0.2976)	(0.1098)	(0.1474)	(0.2447)	(0.0136)
TS_{it}^{X}	-2.7482	0.8633	0.2133	-0.1509	0.2483	-0.5134	-0.6612	0.3545	-0.1809**
Manuf	(2.3353)	(2.3042)	(0.5708)	(0.7665)	(0.8694)	(1.0000)	(0.8422)	(1.2065)	(0.0771)
TS_{it}^{M}	-0.4914***	-0.1362	0.0657	-0.0708	0.5220***	0.2766*	-0.5060*	-0.0648	-0.0947
All	(0.1419)	(0.3246)	(0.0861)	(0.0926)	(0.1641)	(0.1769)	(0.3124)	(0.1716)	(0.0679)
TS_{it}^{X}	-0.8153	-0.7911	0.0846	-0.3513	1.7903*	0.2121	-0.9579*	0.7498	-0.2526
All	(1.3292)	(1.3672)	(0.1502)	(0.3365)	(1.0218)	(0.4074)	(0.6100)	(1.0093)	(0.4726)

This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific exit rate (in percentage points). Exit rates are measured as the ratio of the total of workers exiting an establishment locally in a given year, in a specific occupation group, over the total number of exiting workers in a given year locally. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Robustness

Estimating imports and exports exposure effects separately

In this section, I report estimates of Equation (1.3) when local import exposure is not included in the set of controls. The goal of this section is to emphasize the role of this additional control in the main analysis of Section 1.4.

Table D1: Impact of trade exposure on occupation groups

	Dependent variable: change in local employment *log points*			
Mean =	*2.23 (-0.89)*	*-2.19 (0.76)*	*2.76 (4.04)*	*8.03 (14.06)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	0.6654*	-1.1372	1.1872***	0.7671**
	(0.4500)	(1.4100)	(0.3500)	(0.3600)
TS_{it}^{M} *All*	0.2785	-0.7609	0.2033	0.3457
	(0.6300)	(1.1400)	(0.2500)	(0.3000)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	-2.4805	-9.8977*	-3.4232	-4.0507
	(3.6300)	(6.0000)	(3.2900)	(3.8200)
TS_{it}^{M} *All*	-2.5504	-6.5983*	1.9483	-0.7415
	(2.4000)	(3.8700)	(1.7200)	(1.9100)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific log employment (in log points). Import exposure is estimated separately for China and Eastern Europe and instrumented with "Inst" countries imports. Standard errors are measured with the `ivreg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020a.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D2: Impact of trade exposure on entry flows

	Dependent variable: change in local entry rate *percentage points*			
Mean =	*-0.64 (-1.78)*	*-1.18 (-1.32)*	*0.55 (-0.98)*	*1.53 (3.65)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	-0.0869	-0.2045*	-0.0786	0.0540
	(0.1100)	(0.1200)	(0.0800)	(0.1200)
TS_{it}^{M} *All*	-0.0167	-0.0988	-0.0040	-0.0026
	(0.0500)	(0.0900)	(0.0600)	(0.1900)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	0.0612	0.6267	-0.4063	0.2448
	(0.5600)	(0.8100)	(0.5900)	(0.5500)
TS_{it}^{M} *All*	0.0769	-1.0016**	0.3012	0.3947
	(0.2700)	(0.5000)	(0.3500)	(0.6300)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific entry rate (in percentage points). Entry rates are measured as the ratio of the total of workers entering a new establishment locally in a given year, in a specific occupation group, over the total number of entrant in a given year locally. Import exposure is estimated separately for China and Eastern Europe and instrumented with "Inst" countries imports. Standard errors are measured with the `ivreg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020a.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D3: Impact of trade exposure on exit flows

	Dependent variable: change in local exit rate *percentage points*			
Mean =	*-0.12 (-1.64)*	*-2.31 (-1.63)*	*0.53 (-0.89)*	*1.93 (3.48)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	0.1578	-0.1492	-0.1151	-0.0983**
	(0.1300)	(0.1800)	(0.1000)	(0.0500)
TS_{it}^{M} *All*	-0.0425	-0.0048	-0.0473	0.0646
	(0.0400)	(0.0500)	(0.0700)	(0.0600)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	-0.0330	-0.0466	$2.34e^{-4}$	-0.1716
	(0.5800)	(0.8800)	(0.6500)	(0.5000)
TS_{it}^{M} *All*	-0.2534	-0.4794	0.1990	-0.0046
	(0.3000)	(0.3900)	(0.4000)	(0.5100)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific exit rate (in percentage points). Exit rates are measured as the ratio of the total of workers exiting a given establishment locally in a given year, from a specific occupation group, over the total number of exiting workers in a given year locally. Import exposure is estimated separately for China and Eastern Europe and instrumented with "Inst" countries imports. Standard errors are measured with the `ivreg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020a.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D4: Trade exposure effects on vacancies posted

	Long-run change in regional vacancies posted *percents - Mean = -47.96*					
	Eastern Europe			China		
	(1) (IV)	(2) (IV)	(3) (OLS)	(1) (IV)	(2) (IV)	(3) (OLS)
TS_{it}^{M}	4.4280	4.4280***	1.7187	-14.4934	-14.4934***	-3.8538
	(4.0879)	(1.3005)	(2.9620)	(16.5328)	(5.8461)	(3.0905)
% manuf. tradable goods		-10.0984	-9.9480		-10.1171	-10.0384
		(7.6080)	(7.8772)		(7.5942)	(7.9070)
% routine workers		55.5297	70.9856		66.3858	63.7116
		(103.3285)	(109.1579)		(93.7474)	(103.914)
% female workers		446.173*	455.6374*		465.0634*	457.6881*
		(249.6308)	(256.3220)		(262.3827)	(261.3849)
% foreign workers		-1378.5040*	-1367.0980		-1201.9870	-1324.1320
		(748.3038)	(862.2947)		(853.6149)	(831.8140)
% collective agreements est.		-0.3914	-0.4117		-0.3794	-0.3998
		(0.3498)	(0.3577)		(0.3546)	(0.3644)
% est. w/ work council		-0.2721	-0.2664		-0.2577	-0.2636
		(0.3333)	(0.3076)		(0.3058)	(0.3020)
Time × State FE	✓	✓	✓	✓	✓	✓
Sectoral cluster	✓		✓	✓		✓
R^2	0.1788	0.1788	0.1527	0.1525	0.1525	0.1528
N	874	874	867	874	874	869

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the total number of vacancies posted. Trade exposure is estimated separately for China and Eastern Europe. In columns (1) and (4) the estimated regression only clusters standard errors at the state level. As a result, only the main coefficient and its standard errors are reported (as all other controls are estimated the same). In column (2) and (5), standard errors are measured with the `ivreg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020a. Columns (3) and (6) report the full specification estimated with OLS and standard errors measured with the `reg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020b.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D5: Impact of trade exposure on vacancy posting by occupation groups

	Dependent variable: change in local vacancy share			
	percentage points			
Mean Manuf. =	*-18.65*	*-1.77*	*17.33*	*-2.23*
(Mean All =)	*(-14.34)*	*(2.83)*	*(10.88)*	*(-4.25)*
Exposure to Eastern Europe				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	1.3786	0.5559	-2.6785	4.9816
	(20.9100)	(4.2329)	(4.4786)	(7.2915)
TS_{it}^{M} *All*	0.9510	-0.0348	-0.0619	4.2430
	(4.5300)	(0.2000)	(0.2300)	(3.7348)
Exposure to China				
	Skilled blue collars	Unskilled blue collars	Skilled white collars	Unskilled white collars
TS_{it}^{M} *Manuf*	-0.0048	1.0347	-1.8877**	4.4476
	(3.3300)	(0.9200)	(0.9188)	(3.1600)
TS_{it}^{M} *All*	-0.7200	-1.8566	2.6108*	-2.0423
	(1.3600)	(1.3200)	(1.6100)	(1.9300)

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific vacancy share (in percentage points). Vacancy shares are measured as the ratio of the total number of vacancies posted by local establishments in a given year, for a specific occupation group, over the total number of vacancies posted in a given year locally. Import exposure is estimated separately for China and Eastern Europe and instrumented with "Inst" countries imports. Standard errors are measured with the `ivreg_ss` Stata package from Adão, Morales, Kolesár, and Zhang 2020a.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

County-level results

In this appendix, I briefly report two sets of estimates obtained when the geographic unit of analysis is a county (*Kreis*) rather than a commuting zone (*Arbeitsmarktregion*). The concern with county level analysis was that these geographic units would be too small to prevent significant movements across regions in response to import competition, thereby biasing the estimated causal effect downwards. As it turns out in Tables D6 and D7, the results are robust to considering this finer geographical division of German local labor markets.

Table D6: Manufacturing employment effects of trade exposure

	Long-run change in manufacturing employment *log points - Mean = 0.95*			
	Eastern Europe		China	
	(1) (IV)	(2) (OLS)	(3) (IV)	(4) (OLS)
TS_{it}^{M}	2.4592	0.0321	-6.2335**	-0.1502
	(1.9779)	(0.6587)	(3.0622)	(0.3882)
TS_{it}^{X}	-9.1276*	-0.8890	-18.4134	-1.6521
	(6.6154)	(0.6617)	(15.9044)	(1.4537)
Time × State FE	✓	✓	✓	✓
R^2	0.0214	0.0685	0.0001	0.0689
N	1,362	1,353	1,362	1,353

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the county-level 5-year change in the log of manufacturing employment (in log points). Trade exposure (both in terms of imports and exports) is estimated separately for China and Eastern Europe. In column (1) and (3), trade exposure measures are instrumented with a 2SLS estimator. Columns (2) and (4) report the full specification estimated with OLS. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative groups of countries in the IV

In this appendix, I consider whether the set of instrumenting countries used in the main results is perhaps too restrictive. I therefore construct an alternative set of instruments in which I use all the countries available in the BACI database, excluding

Table D7: Trade exposure effects on vacancies posted

	Long-run change in regional vacancies posted *number of vacancies - Mean = -32.89*			
	Eastern Europe		China	
	(1) (IV)	(2) (OLS)	(3) (IV)	(4) (OLS)
TS_{it}^{M}	12.2778*	3.7395*	-7.5214	-1.7573
	(8.8567)	(2.4922)	(7.2922)	(1.4213)
TS_{it}^{X}	-43.3027*	-0.2777	14.0119	4.2040
	(30.3503)	(1.3173)	(35.8689)	(3.6252)
Time × State FE	✓	✓	✓	✓
R^2	0.1621	0.1339	0.1864	0.1336
N	1,278	1,269	1,278	1,269

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the county-level 5-year change in the occupation-specific vacancy share (in percentage points). Vacancy shares are measured as the ratio of the total number of vacancies posted by local establishments in a given year, for a specific occupation group, over the total number of vacancies posted in a given year locally. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator. Standard errors are clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

only EU members and the United States. Table D8 reports the first stage in this context, and Tables D9 and D10 reveal that the estimates are also robust to this alternative IV strategy.

Table D8: Instrumental variable strategy - First stage using all countries

	Eastern Europe			China		
	Coeff.	R-squared	F-test	Coeff.	R-squared	F-test
$TS_{it}^{M,inst}$	0.2236***	0.6314	4,502	0.0924***	0.1966	3,496
	(0.0355)			(0.0232)		
$TS_{it}^{X,inst}$	0.1724*	0.3543	447	0.0401**	0.3668	1,788
	(0.1069)			(0.02122)		

Note: This table reports the estimated coefficient, standard deviation, R^2 and F-statistic for a regression of the form:

$$TS_{it}^{h} = \alpha_0 + \alpha_1 TS_{it}^{h,inst} + +\alpha_2 TS_{it}^{-h} + X_{it}'\alpha_3 + u_{it}$$

where i denotes local labor market i, h denotes import (respectively export) exposure measure and associated instrument while $-h$ denotes the fact that the baseline specification is explicitly controlling for export (respectively import) exposure, and X_{it} includes the following controls: share of local manufacturing employment, share of female workforce, share of foreign workforce, share of routine workforce, share of establishments tied by a collective agreement, and state (*Bundesland*) × year fixed-effects. Standard errors are clustered at the Federal state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.011$

Table D9: Manufacturing employment effects of trade exposure

	Long-run change in manufacturing employment *log points - Mean = 2.24*			
	Eastern Europe		China	
	(1) (IV)	(2) (OLS)	(3) (IV)	(4) (OLS)
TS_{it}^{M}	5.1602**	0.2040	-6.8258***	-0.9932*
	(2.2169)	(1.0633)	(2.5858)	(0.5641)
TS_{it}^{X}	-17.3604**	-1.2352	-27.1137	-0.3199
	(7.3361)	(1.5693)	(21.7825)	(1.3920)
Time × State FE	✓	✓	✓	✓
R^2	0.0001	0.1072	0.0001	0.1092
N	913	905	913	905

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the log of manufacturing employment (in log points). Trade exposure (both in terms of imports and exports) is estimated separately for China and Eastern Europe. In column (1) and (3), trade exposure measures are instrumented with a 2SLS estimator, using all countries available in the initial BACI database, excluding EU member states and the U.S. Columns (2) and (4) report the full specification estimated with OLS. Skilled workers are defined as workers with a vocational or university degree. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D10: Trade exposure effects on vacancies posted

	Long-run change in regional vacancies posted *number of vacancies - Mean = -47.96*			
	Eastern Europe		China	
	(1) (2SLS)	(2) (OLS)	(3) (2SLS)	(4) (OLS)
TS_{it}^{M}	46.8402**	1.1362	-31.8321*	-4.0421
	(23.5971)	(4.2110)	(19.2547)	(3.2923)
TS_{it}^{X}	-169.2415**	1.9043	3.6022	6.0929
	(80.3797)	(6.0665)	(46.3574)	(10.1088)
Time × State FE	✓	✓	✓	✓
R^2	0.0025	0.1546	0.1426	0.1550
N	878	871	878	871

Note: This table reports estimates from Equation (1.3) when the outcome variable ΔY_{it} is the regional 5-year change in the occupation-specific vacancy share (in percentage points). Vacancy shares are measured as the ratio of the total number of vacancies posted by local establishments in a given year, for a specific occupation group, over the total number of vacancies posted in a given year locally. Trade exposure is estimated separately for China and Eastern Europe. In all cases, trade exposure measures are instrumented with a 2SLS estimator, using all countries available in the initial BACI database excluding EU members and the U.S. Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

FDI and Onshore Task Composition:

Evidence from the Universe of German Firms with Affiliates in the Czech Republic[1]

2.1 Introduction

It has become widely agreed among economists that globalization affects the domestic labor demand. Multinational enterprises (MNEs) are important players for these adjustments, since they source the tasks for production internationally and thus act as a catalyzer for local demand shifts. From a theoretical perspective, the international reallocation of tasks has ambiguous effects on the onshore demand of MNEs: while the increased sourcing of foreign tasks may substitute domestic labor, cost savings from imports pushes productivity up and may induce scaling effects with expansions of domestic tasks (Grossman and Rossi-Hansberg 2008). The effect of trade in tasks on domestic employment is, hence, an empirical question. It has been approached by

[1]Co-authored with Konstantin Koerner (Humboldt University of Berlin, Institute for Employment Research, University of Regensburg).
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many papers that used proxies of task trade such as imported inputs (e.g., Hummels et al. 2014) or foreign direct investments (FDI) (e.g., Kovak, Oldenski, and Sly 2018; Muendler and Becker 2010). Thereby, workers are often distinguished with respect to the international tradability of their job, which has been approximated by a worker's skill level or whether the worker is associated with production (Feenstra and Hanson 1999), a job's offshorability (see, e.g., empirical works by Blinder and Krueger 2013; Brändle and A. Koch 2017), or task profile such as routineness, interactivity or production (e.g., Becker, Ekholm, and Muendler 2013). The variety of these measures is vast and often underlies the subjective categorizations of researchers or experts to classify each tasks as tradable.[2]

In this paper, we depart from subjective categorizations. Specifically, we directly analyze how a firm's FDI to a low-wage country changes its domestic demand of a given task (e.g., Legal analysis, Measuring, Selling), thanks to our unique dataset of the universe of German firms with affiliates in the Czech Republic. The key challenge of identifying this effect is to account for the endogeneity of the FDI decision and firms self-selection into the MNE status. While some MNE characteristics such as high productivity and large size have been broadly studied (e.g., Helpman, Melitz, and Yeaple 2004; Antràs and Rossi-Hansberg 2009), surprisingly little is known about the typical task intensities in these firms and how they differ from non-MNEs. We fill this gap by developing a novel two-step matching strategy that explores the effective shifts of MNEs' task composition in response to FDI.[3]

In the fist step, we explore the particular task intensities of FDI-engaging firms at the brink of their international expansion and obtain a notion of FDI-*facilitating* tasks, i.e., tasks that are susceptible of increasing the benefit/cost-ratio of FDI.

[2] *It is regrettably the case that there are almost as many distinct task classifications as there are papers in the task literature.* Autor 2013, p.195

[3] The two-step matching procedure should not be confused with two-step estimations as in instrumental variable approaches or regarding selectivity akin to the procedure by Helpman, Melitz, and Rubinstein 2008 to estimate a gravity equation. We use two steps for matching and account for this non-random sampling by clustering standard errors at the match level.

Specifically, we use a logit regression with a least absolute shrinkage and selection operator (LASSO) and apply it to narrow the manifold firm characteristics down to a data-driven specification that identifies task intensities with high predictive power for FDI decisions (dynamic correlations).[4] From a cross-validation exercise of 250 logit-LASSO regressions, we select the model with the highest predictive power and then take the obtained propensities of conducting FDI to match the MNEs to firms that have not invested in any foreign country (non-MNEs).

The model selection greatly improves the quality of the matches and, hence, mitigates concerns on firms' engodenous selection into FDI-engaging status. Employing the matched sample, in a second step, we perform a difference-in-differences (DiD) analysis to reveal how FDI changes the MNEs' task intensities relative to non-MNEs. Our estimates provide us with a data-driven metric that identifies tasks and occupations most susceptible of experiencing demand shifts in response to FDIs.

Our new approach is possible because it leverages a newly available dataset compiled by the Institute for Employment Research (IAB), namely the *Research on Locational and Organizational Change* (IAB-ReLOC).[5] It contains the universe of German firms with affiliates in the Czech Republic as of 2010, as well as detailed information on the onshore employment in terms of occupations of these firms, that we link to survey data about the specific task content of jobs. Besides the exact dates of the FDI, the dataset follows these firms from 1985 to 2011, and is designed for event studies. For the same period it also includes a stratified sample of reference firms with no foreign affiliate or indirect foreign investments oversampling larger firms within industries to make them comparable to the MNEs. The choice of the Czech Republic

[4] An approach suggested by Athey and Imbens 2019 or Mullainathan and Spiess 2017 and so far mostly used in the forecast literature as in Verme 2020.

[5] The data are confidential, but can be accessed for non-commercial research upon application via on-site use at the IAB.

is due to a marked wage differential to Germany and because it accommodates the increasing significance of Central European states for FDI by German firms.[6]

The data has several advantages for an analysis of MNEs' onshore employment. First, German MNEs have a substantial weight in the global economy and account for 87% of revenue concentration within Europe (Melitz 2020, p.11).[7] Second, compared to other prevalently used FDI-data for Germany, it is not impaired by selectivity concerns with respect to small or medium-sized companies. Third, we do not have to merge it with trade measures in coarse industry classifications, but already have detailed firm-level information on FDI. Finally, the German occupations can straightforwardly be mapped to task information in the BiBB Employment Survey, which has already been used in prominent task analyses (Spitz-Oener 2006; Becker, Ekholm, and Muendler 2013; Becker and Muendler 2015). Unlike other precise employer-employee data such as for Denmark or France, we thus do not need to employ several crosswalks to map jobs to the American O*net directory.[8] Both datasets are derived from the same population, i.e., employees in Germany, so we have no extra noise from occupational differences in task performance across countries.

We find that high task intensities in (labor) legislation, management, and administrative tasks come along with a firm's decision to engage in FDI. These tasks seem to increase the firms' capability of bearing the high (fixed) costs of conducting FDI, suggesting that an important share of the organizational costs of international

[6]Reports by the Deutsche Bundesbank 2014 estimates that the Czech Republic accounts for 24 percent German MNEs' workforce in the Central and Eastern European Countries.

[7]The concentration is measured by a Herfindahl–Hirschman Index for data from 2000-2017. See also Bighelli et al. 2020.

[8]By the Danish employer-employee data, we refer to the administrative registers at Statistics Denmark, which include Firm Statistics Registers (FirmStat), and the Integrated Database for Labor Market Research (IDA). The respective data for France is available in the Panel for Annual Declaration of Social Data by the INSEE. In the U.S., MNE data rarely contain information on occupational titles, which are needed for the analysis of task. We think for example of the BEA Survey of Direct Investment Abroad, which does not include information on the workforce composition.

coordination pertains to legal contracting (labor legislation), management, and international coordination.[9]

The matched DiD design then allows us to identify the MNEs' shifts in task intensities relative to non-MNEs. For manufacturing MNEs, we find relative decreases in employment of low-wage production-related tasks such as Monitoring, Producing, Measuring, and Repairing. In service MNEs, the declining task intensities are also those with below-average wage compensations. We find employment decreases in some typical service tasks such as Informing, tasks requiring Medical knowledge (in the private non-health service industries, e.g., medical analysis laboratories), and Repairing. On the positive side the estimates show, regardless of the economic sector, that MNEs increase headquarter activities such as Organizing others and Analyzing which are also tasks that positively correlate with future FDI decisions (e.g., Management) in the logit regressions.

To generalize our insights, we finally take stock of the literature on job offshorability and compare the actual employment shifts in response to FDI with established measures of offshorability by Blinder and Krueger 2013 (BK hereafter), Becker, Ekholm, and Muendler 2013 (BEM), Brändle and A. Koch 2017 (BrKo), and jointly ALM and Spitz-Oener 2006 (ALM-SO). We normalize the measures and re-run our matched DiD to explore how the relative shares of offshorable jobs react to FDI. We find a majority of negative employment effects in both sectors, but with some notable exceptions. To shed more light on the overlap of these measures with what we label as FDI-substitutability, we leverage the fact that the offshorabiliy measures are based on occupational categories. We assess the rank correlation of the respective offshorability measures with a ranking that we obtain from the matched DiD approach using 93 occupational categories as dependent variables. In the manufacturing sector, the strongest overlap persists with the routine manual index (by ALM-SO), while all mea-

[9] Antràs 2005 and Helpman, Melitz, and Yeaple 2004 highlight the trade-off between contract incompleteness with foreign suppliers and organizational fixed costs.

sures of routineness, and lack of interactivity show positive correlation. The overlap in the service sector is highest with the routine non-interactive index (by ALM-SO), but exists for all measures based on routine-content.

Literature

Our paper integrates well in a large and expanding body of literature on the effect of international integration on domestic labor demand. Offshoring affects individual employment, labor market transitions, or wages as shown, for example, by Geishecker 2006 for Germany, P. Egger, Pfaffermayr, and Weber 2007 for Austria, Munch 2010 for Denmark, or Feenstra and Hanson 1996 for the US. The majority of papers from this strand of literature focuses on the effect of arm's length trade in the manufacturing sector and on skill groups. Ebenstein et al. 2014 and Baumgarten, Geishecker, and Görg 2013 move the focus to the occupation level, which can explain a higher fraction of the labor market changes induced by offshoring, and include measures for non-routine and interactive tasks. We expand the scope of the analysis by considering the German service sector as, for example, Eppinger 2019. Instead of measuring cross-border flows of service firms however, we consider FDI, which we suspect to be a more precise measure for capturing the effects of globalization in the service sector, because not all cross-border exchanges of service activities can be quantified by flow data (for example, an information or consultation can be exchanged on the phone and be firm-internal without any direct cross-border payment).[10] Our approach is more similar to Liu and Trefler 2019 who analyze U.S. service offshoring with FDI, or Becker, Ekholm, and Muendler 2013 who analyze onshore employment changes in FDI-conducting MNEs monotonically along indices that quantify non-routine or interactive occupations (but not directly tasks). In a subsequent work, Becker and

[10]The majority of international statistics on trade in services uses FDI as primary source of measurement. See for example the Manual on Statistics of International Trade in Services from OCDE et al. 2010.

Muendler 2015 study offshoring effects separately for the tasks from the BiBB Employment survey to show the growing specialization of the German workforce into non-offshorable workplace activities and knowledge requirements. They however only propose an industry-level analysis, whereas we can directly map tasks to the MNEs' workforce and analyze the effect of FDI at the firm level.

Most of the offshoring literature on input trade (e.g., Hummels et al. 2014; Dauth, Findeisen, and Suedekum 2014; Kovak, Oldenski, and Sly 2018; Bernard, Fort, et al. 2020) addresses endogeneity concerns via instrumental variable strategies (IV). Since our outcome variables are a battery of different tasks, it becomes difficult to construct time-varying firm-level instruments for our treatment variable FDI that fulfill the validity assumption for each task. The high quality of our data, especially regarding FDI dates, also mitigates any measurement bias in the independent variables. Thus we see no benefits of an IV approach (which comes with other downturns) over our matched DiD approach.

Our focus on employment recomposition also contributes to the literature on job polarization with seminal works on skill-biased technical change by ALM and Autor, Katz, and Kearney 2006. This change has been narrowed down to the disappearance of routine jobs, which represent a large fraction of middle income jobs (Cortes 2016; Cortes, Jaimovich, and Siu 2017; Cortes, Jaimovich, Nekarda, et al. 2020; Atalay et al. 2020), that become either automated (Dauth, Findeisen, Suedekum, and Woessner 2017; Autor and Salomons 2018; Graetz and Michaels 2018), or moved to low-wage countries (Cortes and Morris 2020). While we cannot trace the aggregate cross-border movements of middle-income jobs (since the IAB-ReLOC does not record the affiliates' employment sufficiently well), our negative estimates still provide evidence of a relative decrease in the demand for low- and medium-wage production tasks in German MNEs. It also adds to the discussion on workplace specialization (Cortes and Salvatori 2019; Becker, H. Egger, et al. 2018; Bernard, Fort, et al. 2020), since we also

find that FDI to a low-wage country expands the intensity of high-wage social tasks such as management, and commercial-related activities. The growing importance of these social tasks in the long-run trend of within-firm job polarization has been recently emphasized by Cortes, Jaimovich, and Siu 2020.

We link the task approach from this strand of literature to the very related field focused on the identification of job offshorability. This literature mainly addresses questions on how many and/or which jobs could potentially be performed from abroad and has predominantly been based on subjective judgment on the set of occupational activities (Blinder 2009; Blinder and Krueger 2013), or tasks (Brändle and A. Koch 2017; Hummels et al. 2014; Becker, Ekholm, and Muendler 2013) that can be labeled offshorable, or uses other measures such as geographical concentration (e.g., Jensen and Kletzer 2010) or the use of information and communication technology (e.g., Van Welsum and Vickery 2005) to establish job offshorability. There is essentially a trade-off between the subjective and forward looking analysis of *potentially* offshorable jobs and a data-driven positive approach of which jobs have been actually traded. In this paper we choose in favor of the latter and observe which tasks respond in the domestic part of the MNE when it invests in a low-wage country. This approach then enables us to compare observed employment shifts to indices of offshoring potential from the literature.

The remainder of the paper is structured as follows. We present the dataset in Section 2.2. Section 2.3 analyzes which task intensities correlate with a FDI decision using the logit-LASSO approach, and discusses the basis of potential selection bias at the task level. In Section 2.4, we match firms by propensity scores and use a difference-in-differences design to identify the employment adjustment of onshore tasks to FDIs. We compare our results with the measures of "job offshorability" in Section 2.5. Finally, Section 2.6 concludes.

2.2 Data and Descriptive Statistics

In this section we introduce the various sources of our dataset and explain the occupational classifications and measures of task content used.

2.2.1 ReLOC

The unique and well-suited dataset for our analysis is derived from several administrative sources that were compiled within the scope of the IAB ReLOC-project. The data contains the universe of German MNEs with one or more affiliates — having an ownership share of at least 25 percent — reported in the Czech Commercial Register as of August 2010 with precise information on the date of the FDI, but no information about the type of FDI (vertical, e.g., efficiency seeking or or horizontal, e.g., market seeking) or on arm's length trade of the firm.[11] Prerequisites for a company to be assigned to the reference group are that it should have (i) no direct investment in a foreign company, (ii) no foreign sister company and (iii) no indirect investment abroad. Since the reference group is directly built to approximate size and industry distributions of the MNE group, the sample of non-MNEs is stratified and over-samples medium-sized and large firms by industry. We focus on the manufacturing and private service sector, which includes 1,834 German MNEs and 7,180 non-MNEs during our observation period from 1985 to 2011.[12]

German firm names are linked to the IAB Establishment History Panel following precisely the record linkage procedure described by Schäffler 2014. The establishment data are derived from administrative accounts at the German Federal Labor Agency and contain plant-level information on the industry classification, location and foundation date of each establishment. For multi-site firms, we choose the re-

[11] The sample does not include MNEs that exited before, or entered after 2010. See Hecht, Litzel, and Schäffler 2013 for more details on the compilation of the treatment and control group.

[12] East German firms are recorded from 1992 onwards.

gion and industry that cover the highest proportion of the firm's employment. We directly connect the plants with employment information of the IAB Integrated Employment Biographies, which covers all employees from the German social security system, thanks to a readily available plant identifier. In terms of magnitudes, the MNEs in our sample employ 1.9 million workers (in 2008), or about 6 percent of all workers in Germany subject to social security. The worker-level information includes daily wages, gender, age, labor contract type (marginal, part- or full-time) and, most importantly, up to 330 (3-digit) occupation codes (*Klassifikation der Berufe 1988, KldB88*). These can be linked to on-the-job task and knowledge requirements from the *BiBB Employment Survey*.

2.2.2 BiBB Employment Survey

The BiBB Employment Survey is a representative cross-section of the German labor force that asks workers about their career history and detailed workplace and job characteristics such as working conditions, formal qualifications, other knowledge requirements, and the specific tasks performed on the job. They are conducted every six years by the Institute for Vocational Education and Training (BiBB) and other institutes such as the IAB or the Federal Institute for Occupational Safety and Health.[13] The longitudinal scope of the survey is limited due to changes in the methodology between the waves, with only a fraction of questions being repeated throughout the different waves. We therefore focus solely on the wave of 1998/1999. In this survey, workers answer the following generic questions about job tasks on a 1-3-scale ("often", "rarely", "never"):

> Would you say that you perform the following activity in your job? How often?

[13]Formerly the survey was named German Qualification and Career Survey. Waves are available for the years 1979, 1985/86, 1991/92, 1998/99, 2006, and 2012. Each wave covers between 20,000 and 35,000 individuals.

Or about knowledge requirements on a binary scale (yes-no):

> In which areas do you need special knowledge in your current job, not just basic knowledge?

Since the frequency of the task's performance may be unrelated to its importance for the job, we convert the answers to binary responses $\{0; 1\}$, that is, the worker either performs (even rarely) or does not perform a particular task.[14] We then take the average of affirmations per three-digit occupation codes and consider that a given occupation is associated with that task or knowledge if the positive responses exceed 50 percent of all responses.[15] We proceed similarly for the type of knowledge requirements.[16]

2.2.3 Summary statistics

The dataset contains a total of 161,186 firm-year observations, with similar numbers of firms in the manufacturing and the private service sector. Table 2.1 provides an overview of the industry codes of the MNEs within the manufacturing and the private service sector. Within the manufacturing sector, the majority of MNEs belongs to the metal, machine, optic, or electronic industries. Table A3 further reports summary statistics about the firms' characteristics by MNE status and by sector. Two

[14] See Table A1 in Appendix A for a description of the tasks in the BiBB survey of 1998, the associated average wages of all workers that perform it, and examples on representative jobs. The best paid task is *Developing and researching*, while *Producing* is the worst paid. Regarding knowledge content, we observe that *Management* skills are at the top of the wage distribution, and that *Other specialized* or *Medical* knowledge are at the bottom (note that these numbers are derived from the manufacturing and private service sector; the health industry with predominantly public firms is excluded.

[15] Becker, H. Egger, et al. 2018 propose an imputation method to map tasks from the BiBB Employment Survey to employment data. Although their approach may be more rigorous, it is motivated by their specific model of heterogeneous task contents within occupations and across firms. In our analysis, we do not allow for such variability, and we match treated and control firms on characteristics that would have been otherwise used in the imputation method. Consequently, our results are insensitive to the choice of mapping algorithm.

[16] For the sake of brevity we subsume the term knowledge requirements as tasks in the subsequent analyzes.

Table 2.1: MNEs' Classifications of Economic Activity

	Number of	
Manufacturing sector (ISIC rev. 3)	MNEs	non-MNEs
Food products, beverages and tobacco (15-16)	37	446
Textiles, leather, and related products (17-19)	66	114
Wood and wood products (20)	34	91
Pulp, paper and paper products; publishing and printing (21-22)	66	322
Coke, refined petroleum products and nuclear fuel (23)	4	8
Chemicals, chemical products and man-made fibres (24)	79	156
Rubber and plastic products (25)	107	193
Other non-metallic mineral products (26)	59	109
Basic metals and fabricated metal products (27-28)	237	625
Machinery and equipment n.e.c. (29)	204	522
Electrical and optical equipment and machinery (30-33)	226	413
Transport equipment and motor vehicles (34-35)	53	114
Not elsewhere classified, recycling (36-37)	37	132
Service sector (ISIC rev. 3)		
Sale, repair of motor vehicles; sale of automotive fuel (50)	51	263
Wholesale trade, except motor vehicles (51)	467	704
Retail trade, except motor vehicles; repair household goods (52)	127	571
Hotels and restaurants (55)	14	40
Transport (60-62)	35	147
Storage; communications (63-64)	147	260
Financial intermediation (65-67)	29	291
Real estate activities (70)	54	144
Renting of machinery, equipment, vehicles, household goods (71)	13	30
Computer and related activities incl. data processing (72)	70	146
Research and development (73)	6	41
Accounting, book-keeping, legal; market research; consulting* (74.1)	139	360
Technical consulting, testing and analysis; architectural, engineering (74.2-74.3)	95	232
Advertising (74.4)	20	66
Labour recruitment, provision of personnel, cleaning, security, and other (74.5-74.8)	73	598

Notes: This table reports frequencies of MNEs by economic activities based on the International Standard Industrial Classification (ISIC rev. 3).
*Specifically, consulting in this industry includes business/management/tax advisory activities.

years prior to a FDI, manufacturing MNEs employ on average about 814 workers who perform approximately 21.5 different tasks altogether or 5.1 different tasks each. In comparison, respective non-MNEs from our stratified sample are on average smaller (222 workers), but perform a similar amount of different tasks per firm (20.3) or per worker (4.8). To sketch the firms' labor input, we study task intensities in firms' workforce, that is, a task's share in all tasks performed in the firm.[17] In all manufacturing

[17]In Appendix A, we also present employment composition in terms of broad occupational categories that classify jobs by typical education-level, earnings, and job activities according to Blossfeld 1985 (see Table A2 for a definition of these categories).

firms, we find the highest intensities in Organizing others, Consulting/informing, Measuring, Monitoring, Repairing, or Manufacturing. These tasks seem to be the basis for a manufacturing firm's production. The standardized bias (resp. variance ratio) further informs us about groupwise differences in mean (variance) and the balancing of the sample.[18] Relative to non-MNEs, manufacturing MNEs feature high intensities in high-wage tasks such as Researching and developing, Training others, Analyzing, Management, or Computer engineering.

Within the service sector, most MNEs belong to the wholesale, retail, storage, or communications industries (Table 2.1). The substantial number of MNEs that belong to firms with major activities focused on accounting, book-keeping, legal matters, market research, consulting, or engineering is however also notable. Another important industry (74.5-8) includes recruitment agencies that may allocate Czech labor to projects in Germany (without Czech workers joining the German social security system). The characteristics of service firms are shown in the last three columns of Table A3. A service MNE employs on average 445 workers who perform 16.1 different tasks or 5.5 different tasks each. In the reference group service non-MNEs are smaller on average (143 employees), but perform a similar amount of different tasks per firm (15) or per worker (4.9). Service firms' production uses intensively tasks such as Analyzing, Organizing others, Consulting/informing, or the Use of software. Compared to the manufacturing sector, we find that service firms put more resources on Analyzing, Acquiring customers, Buying and selling, Negotiating, and Serving and caring for others, Marketing, as well as proficient use of the native language (German). Across the service firms, the standardized bias shows that MNEs feature again higher intensities in high-wage tasks such as Researching, Analyzing, Management, Giving presentations. We however, also find intensive use in tasks such as Organizing

[18]The standardized bias is defined as the mean difference divided by the average standard deviation of the two groups: $(\mu_{treatment} - \mu_{control})/(\frac{\sigma^2_{treatment}+\sigma^2_{control}}{2})^{-\frac{1}{2}}$. The variance ratio is: $\frac{\sigma^2_{treatment}}{\sigma^2_{control}}$.

others or the Use of software. We conjecture that these are typical task intensities of more productive firms.

Overall, the summary statistics show stark sectoral differences, that suggest a separate analysis per sector. Since we also observe substantial differences in the task inputs between MNEs and the stratified sample of non-MNEs — the standardized biases are almost systematically larger than $|0.1|$ — any analysis on changes in task intensities is confronted with a selection bias problem. Specifically, if the MNEs' characteristics are typical for more productive firms, the group of all non-MNEs is not suited for looking at counterfactual evolution of onshore employment in response to FDI. To tackle this endogeneity bias, we analyze the relevance of specific task intensities for a future FDI-decision in the next section.

2.3 FDI and Facilitating Tasks

To account for the selection of FDI-conducting firms on observables in our subsequent DiD-analysis, this section analyses the task intensities in MNEs that typically come along with a FDI decision in the near future. We thereby expect to observe high intensities of what we label as FDI-*facilitating tasks*. These are tasks that allow firms to organize the international expansion and thus generate *lower costs* of the FDI (e.g., these firms do not need to hire workers for administrative duties). We can also conjecture, in the context of vertical FDI and production relocation, that MNEs will have high intensities of tasks that are highly offshorable and thus may induce *higher benefits* from the exploitation of labor cost differences (Helpman, Melitz, and Yeaple 2004; Nocke and Yeaple 2008). Alternatively, market-seeking horizontal FDI would come along with high intensities of commercial tasks or no relevant differences between MNEs and non-MNEs.[19]

[19]Presumably the correlation we conjecture here are dependent of the type of FDI (horizontal or vertical) performed. Our data do not allow us to differentiate these types of FDI. We conjecture that vertical integration is more prevalent in the manufacturing sector, whereas horizontal FDIs are

Our empirical strategy aims at identifying tasks that have predictive power for a firm's future FDI decision and at finding the specification of a logit model that provides the best prediction of those events. Subsequently, we use this model in our matching approach and employ it to predict a firm's propensity of conducting FDI. The matching thus alleviates concerns about selection on observables in the DiD analysis.

2.3.1 Empirical Strategy - LASSO-Logit Regression

To identify task intensities that contribute to the likelihood of a firm's FDI decision, we specify a logit regression and add a least absolute shrinkage and selection operator (LASSO) to assess the predictive power of different model specifications of a FDI decision in the near future (two years). Without the LASSO-penalty term, the logit regression has the following form:

$$\ln\left[\frac{\mathbb{P}[\text{FDI}_{f,t+2}=1|\boldsymbol{X_{ft}}]}{\mathbb{P}[\text{FDI}_{f,t+2}=0|\boldsymbol{X_{ft}}]}\right] = \underbrace{\beta_0 + \boldsymbol{\beta_1}'\boldsymbol{\tau_{ft}} + \boldsymbol{\beta_2}'\boldsymbol{c_{ft}} + \delta_i + \gamma_r + \zeta_t}_{\boldsymbol{X_{ft}\beta}} \tag{2.1}$$

where f denotes a firm, t the year of observation and $\boldsymbol{\tau_{ft}}$ is a vector of the firm's intensities of either broad occupational categories, or the tasks from the BiBB survey.[20] The coefficients of interest are thus in $\boldsymbol{\beta_1}$, which captures the predictive power of these intensities for the FDI. $\boldsymbol{c_{ft}}$ is a vector of controls including firm size and other firm characteristics that we discuss below. The parameter δ_i denote industry fixed effects that control for differential exposure to international activities across industries. Jointly with firm size, they also control for the non-random stratification of the reference firms. We thus do not interpret their coefficients. Region fixed effects γ_r control for the proximity to the Czech Republic and other unobserved heterogeneity

potentially present in both sectors. In our analysis, we propose an interpretation of our coefficients for both types.

[20] We use the classification of occupation codes at the coarse level by education level, average earnings and activities performed from Blossfeld 1985. See Appendix A for more details.

related to the location of the firm.[21] Year fixed-effects ζ_t account for common time trends such as the business cycle.

The aim of Equation (2.1) is to identify occupation groups and task intensities that participate of the selection of firms into the MNE status. In order to do so, it seems important to control for other observables that may contribute to the firm's endogenous decision to perform FDI. From the theoretical literature, we know that firm's industry and location, firm's size and growth, firm's labor costs and idiosyncratic productivity are all important factors. As a result, we control in $\boldsymbol{c_{ft}}$ for a firm's number of employees, its wage bill, the number of establishments per firm, and a 4-year employment growth rate, along with aforementioned location and industry fixed effects. In addition to these variables, we include the share of females (to control for within occupational differences regarding tasks as suggested in Black and Spitz-Oener 2010), as well as an additional proxy for firms' fundamentals, namely the four-year growth of the mean wage at the firm. The specification may still suffer from re verse causality, or omitted variables bias. While we alleviate concerns about the former by regressing FDI on lagged values of firm characteristics, the estimation could still be biased from omitted variables that are correlated to both the FDI decision and the initial task intensities. One of such instances could be firm-specific communication costs. If these costs are related to the region, the region fixed effects capture most of the bias. If the omitted variable bias relates to firm productivity, the firm's size, employment growth, and wages controls should capture most of the bias. However, we cannot fully control for all potential confounders and thus refrain from interpreting small differences or magnitudes of the estimates. Finally, we have no information nor theoretical framework to discuss the causality for the differences in task intensities between MNEs and non-MNEs. As a result, a strict causal interpretation of

[21] We distinguish 4 broad regions: North (Bremen, Hamburg, Lower Saxony, Schleswig-Holstein), West (Hesse, North Rine-Westphalia, Rhineland Palatinate, Saarland), East (Berlin, Brandenburg, Mecklenburg-Western Pomerania, Saxony, Saxony-Anhalt, Thuringia), and South (Baden-Wuerttemberg, Bavaria).

our estimates is subject to caveats. We prefer therefore to interpret our outcomes as suggestive evidence of task-specific selection biases.

We further solve (2.1) for $\mathbb{P}[\text{FDI}_{f,t+2} = 1|\boldsymbol{X_{ft}}]$ and employ the derived transformation function

$$\mathbb{P}[\text{FDI}_{f,t+2} = 1|\boldsymbol{X_{ft}}] = \frac{\exp^{\boldsymbol{X_{ft}\beta}}}{1 + \exp^{\boldsymbol{X_{ft}\beta}}} = F(\boldsymbol{X_{ft}\beta}) \tag{2.2}$$

in the maximized log-likelihood with LASSO-penalization (L1-norm) of $\boldsymbol{\beta_1}$ and standardized regressors in $\boldsymbol{X_{ft}}$:

$$\max_{\boldsymbol{\beta}} \frac{1}{N} \sum_{f} [\mathbb{1}[\text{FDI}_{f,t+2} = 1] \ln F(\boldsymbol{X_{ft}\beta}) + \mathbb{1}[\text{FDI}_{f,t+2} = 0] \ln(1 - F(\boldsymbol{X_{ft}\beta}))] - \lambda||\boldsymbol{\beta_1}||_1, \tag{2.3}$$

The LASSO thereby acts as a model selector aimed at improving the prediction accuracy and interpretability of the regression model by altering the model fitting process through the parameter λ. The penalization pushes coefficients of those task intensities that have small predictive power for the FDI to zero. The higher the λ the higher is the penalty imposed on the task intensities in $\boldsymbol{\beta_1}$ and the higher a variable's contribution to the log-likelihood function must be. If they are weak and/or correlated with other predictors, their coefficients are pushed to zero.[22]

We estimate equation (2.3) on the unmatched sample of firms, but separately for the manufacturing and service sector. Moreover, we only include one observation per MNE, two years prior to the FDI. Thereby, all coefficients in $\boldsymbol{\beta}$ are merely identified by differences to non-MNEs and we avoid undesired attenuation of the estimates due to the autocorrelation of firms' observables. To abstract from any difference in the units of measurement, we standardize all variables in $\boldsymbol{X_{ft}}$ to have mean zero and variance of 1. In the outputs, the estimates are returned to their original scales.

[22]Note that in Equation (2.3), the parameter λ acts as the Lagrange multiplier in a constrained maximization problem where the objective function is the standard logit model, and the constraint is a free parameter that determines the regularization.

In a first step, we run the LASSO-logit regressions sequentially on 50 values of λ, which provides us with models of different sparsities.[23] The penalty parameter λ varies from a restrictively high level — that only allows to consider non-penalized coefficients — over so-called knots where new predictors are successively added towards the standard logit — where λ is 0 and the full set of regressors is included in the model. Figures 2.1 and 2.2 plot the path of the estimated coefficients in $\boldsymbol{\beta_1}$ for various values of λ to depict how the impact of a given task intensity is evolving if others are included or dropped out. For instance, this procedure reveals the single best predictor of future FDI, and informs us whether the direction of the conditional prediction for the FDI (the sign of the estimates) changes along the path towards sparser models.

In a second step, we perform a five-fold cross-validation. This means that we repeat the LASSO regressions five times with each fold using four fifths of the sample and estimating models with 50 values of λ (these values do not change per fold) to assess their out-of-sample predictions on the omitted fifth of the sample. We stratify the data to include a similar number of random MNEs in each fold.[24] The omitted part is changed for each of the five folds, so we have a total of 250 different regressions. We then identify the value of λ associated with the lowest average of the mean squared prediction error (MSPE) over all five folds. This value of λ identifies the specification of the model that best predicts an FDI-decision in the near future. It thus contains a subset of job or task intensities that are correlating with future FDI-decisions, even after conditioning on many other firm characteristics such as size, wages, or industry code.

In a final step, we run a non-penalized logit model employing only the selected subset of covariates, i.e. a post-LASSO regression. We report these coefficients in Tables 2.2 and 2.3. They inform us precisely about the occupational shares or task

[23] We used the Lassopack (Ahrens, Hansen, and Schaffer 2018) available for Stata15.
[24] We applied the random-number seed 12 for the stratification per fold.

intensities susceptible of generating a selection bias in our estimation of onshore employment's response to firms' FDI decisions. The model specification is subsequently used for the computation of firms' propensity scores to conduct FDI, which we will then use in our matched DiD analysis in Section 2.4.

2.3.2 Results - Broad Occupational Activities

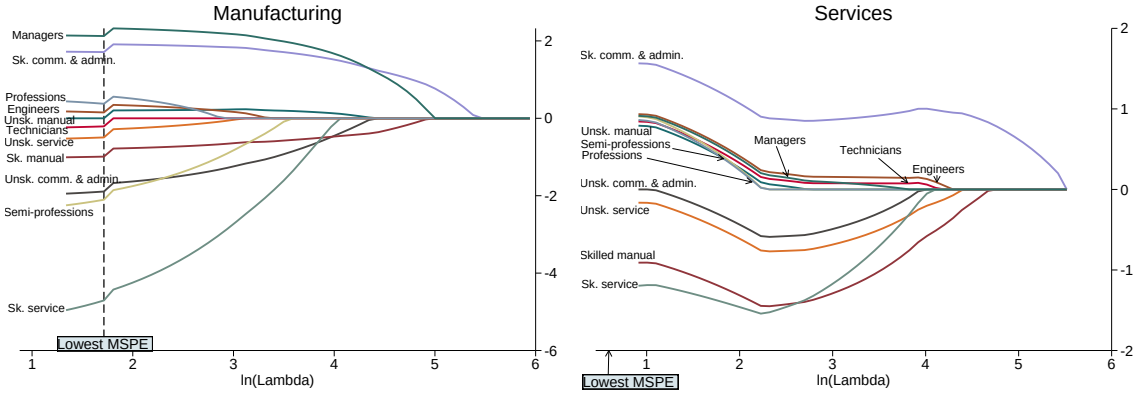
In a first instance, we treat interacting tasks as a fixed set that needs to be preformed jointly within broad occupational groups.[25] Starting with the coefficient paths along 50 values of λ, Figure 2.1 illustrates the evolution of the estimates in $\boldsymbol{\beta_1}$, respectively for the manufacturing and service sector. As λ decreases, the algorithm adds knots, or a larger selection of occupation codes for the prediction of future FDI. A positive (resp. negative) coefficient implies that a high (resp. low) occupational share correlates positively with future FDI decisions conditional on all other covariates. We discuss in turn denser models (towards smaller values of λ), and the best predicting specification according to the lowest MSPE. Notably, the coefficients never change sign (e.g., from positive to negative) along the path towards sparser models, which increases their plausibility.

The left (resp. right) panel of Figure 2.1 presents the results for the manufacturing (resp. service) sector. For both sectors, we find that the share of Skilled commercial and administrative employees is the best single predictor for future FDI (first knot). A high employment share of this group hence increases the propensity of a firm to engage in FDI. In the manufacturing sector, the second most important occupational category is Managers (second knot). On the other hand, high shares of Skilled service, Unskilled commercial and administrative, and Skilled manual occupations are strong negative predictors for FDI in both sectors.

[25] In Appendix C, we repeat this exercise for finer occupational categories (two-digit) to disentangle the margins of heterogeneity hidden in the coarse occupation groups.

Figure 2.1: Coefficient paths of occupational intensities penalized by LASSO

(a) Full coefficient vector (b) Full coefficient vector



Notes: Figure 2.1 displays the value path of estimated coefficients in $\boldsymbol{\beta_1}$ of Equation (2.3) with respect to a broad range of values of the penalty parameter λ. The left (respectively right) panel shows the evolution within the manufacturing (respectively service) sector. Each line corresponds to the path of the estimated coefficient for a specific occupational group (see table A2). The dashed line marks the model with the lowest MSPE (strongest predictive power). It is obtained from testing 50 different values of λ in a five-fold cross-validation.

If we consider the model with the highest predictive power (lowest MSPE) according to the respective cross-validation exercises, we find that only Unskilled manual occupations are excluded in the manufacturing sector, or Unskilled commercial and administrative occupations in the service sector. For the classification of tasks via broad occupational categories, our preferred specification is hence not very different from a standard logit regression.[26] Using the best predicting model, we present the respective estimates of a Post-LASSO regression in Table 2.2.

We find that the strongest positive predictors are also the ones that have the highest statistical significance such as Skilled commercial and administrative occupations and Managers. Both occupational groups feature relatively high wages (see Table A2) and we conjecture that these tasks are FDI-facilitating, in the sense that they are characteristic features of typically more productive FDI-engaging firms and that they reduce the (fixed) costs of FDI.

[26] Unskilled manual occupations represent the largest employment share of manufacturing firms, while Unskilled commercial and administrative tasks are the largest employed group for service firms. It is therefore not surprising that they do not appear in the respective selected sets, as they are both large groups in treated and non-treated firms.

As negative predictors, we observe categories pertaining to low- or middle-income jobs such as Skilled manual, or (Un)skilled services occupations. While we prefer to interpret our correlation as evidence of the typical task intensities of more productive firms, the outcomes are also in line with the offshorability literature that argues that some tasks (in particular services) cannot be traded internationally. [27]

The results are robust to more parsimonious specifications of Equation (2.1). In the manufacturing sector, the results are also robust to including coarser industry fixed effects (at the one-digit level), while it is not the case in the service sector.

2.3.3 Results - Tasks

We now turn to identifying directly the tasks that are strong predictors of future FDI, to provide more detailed information about the potential selection biases emphasized above. Again, Figure 2.2 displays the coefficient paths from $\boldsymbol{\beta_1}$ for varying values of the penalty coefficient λ separately for the manufacturing and service sector. In this section $\boldsymbol{\beta_1}$ contains the coefficients of the task intensities from the BiBB.

In the manufacturing sector three tasks stand out in contributing positively to the propensity to engage in FDI: Legal knowledge, Labor legislation, and Management. We interpret these tasks as FDI-facilitating and crucial for the due diligence of FDI into a new market as well as to manage working processes between parents and affiliates. For instance, MNEs need to analyze the legal and related tax matters of the international expansion, or require labor legislation services for the handling of lay-off protection and hires in the affiliates' country. The best single predictor is the Use of software, while Legal knowledge is added in the second knot and highly significant in

[27] Blinder 2009 gives as an example tasks of (Skilled) service occupations such as hairdressers that cannot be offshored, whereas tasks of (service) Professions such as medical doctors who interpret X-rays are easily performed from abroad. See Table 2 in Blinder and Krueger 2013, p.117. In the preferred measure by the authors (externally coded), only .7% of service occupations are offshorable, while this share amounts to 20.5% for professional, and 80.7% for production occupations. Other weak *and* positive predictors we find such as the share of Professions, Engineers, or, in Service firms, Unskilled manual occupations describe indeed groups with relatively high shares of offshorable jobs.

Table 2.2: Post-Logit-LASSO Results for Occupational Groups.

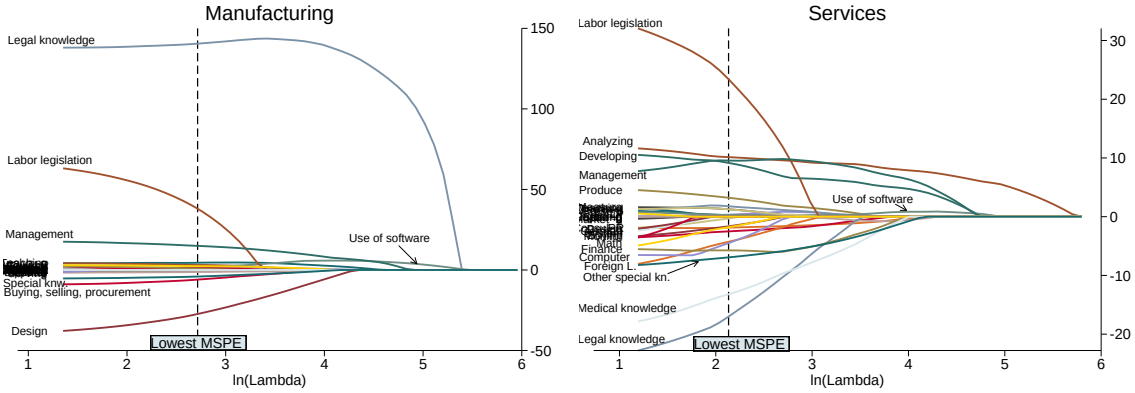
Dep. variable: FDI in 2 years	Post-Logit-LASSO Manufacturing (1)	Services (2)
Production occupations:		
Unskilled manual	-	0.843**
Skilled manual	-1.044***	-0.917**
Technicians	-0.290	0.892**
Engineers	0.232	0.985**
Service occupations:		
Unskilled services	-0.589	-0.152
Skilled services	-5.545*	-1.283
Semiprofessions	-2.580	1.019
Professions	0.565	0.965
Administrative occupations:		
Unskilled commercial and admin.	-2.068***	-
Skilled commercial and admin.	1.742***	1.604***
Managers	2.171***	0.970**
Non-penalized in LASSO:		
log # establishments	0.488***	0.212***
Employment growth	0.0734*	0.172***
Share of females	0.625**	-0.353*
log wage bill	0.0157	0.584***
Mean wage growth	0.0432	0.0757*
log # employees	yes	yes
Region fixed effects	yes	yes
Industry fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	57,532	51,519
log λ of min. MSPE	1.71	0.58

Notes: This table reports the estimated coefficients from a Post-LASSO logit model. The set of included occupational shares is selected by cross-validation finding the model with the lowest MSPE. The MNEs employment size and the industry fixed effects are needed to control for the non-random stratification of non-MNEs. Standard errors are clustered at the treatment level, i.e. firm-level according to Abadie, Athey, et al. 2017.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the model with the highest predictive power (lowest MPSE), as column 1 in Table 2.3 shows. At the other extreme, Design — a task particularly relevant for marketing (e.g., commercial artists) — is a strong negative predictor of future FDI in the manufacturing sector, potentially because productive firms have outsourced marketing departments earlier than their less productive (non-MNEs) competitors. Table 2.3 further reveals negative correlations with FDI for tasks that require local knowledge (networks) or geographic proximity such as Buying, selling and procurement, and Other specialized knowledge.

Figure 2.2: Predictive Power of Task Intensities for FDI

(a) Full coefficient vector (b) Full coefficient vector



Notes: Figure 2.1 displays the value path of estimated coefficients in $\boldsymbol{\beta_1}$ of Equation (2.3) with respect to a broad range of values of the penalty parameter λ. The left (respectively right) panel shows the evolution within the manufacturing (respectively service) sector. Each line corresponds to the path of the estimated coefficient for a task intensity (see table A1). The dashed line marks the model with the lowest MSPE (strongest predictive power). It is obtained from testing 50 different values of λ in a five-fold cross-validation.

In the service sector, the FDI-engaging firms feature high task intensities in high-wage tasks such as Analyzing, Developing and researching, and Management. Besides the Use of software, these tasks appear early in the sequential process (lowest knots) and their contributions remain relatively high even after moving to richer models. In higher knots, knowledge in Labor legislation is added and also has a strong positive contribution to the propensity of FDI, while Legal expertise shows strong negative correlations with FDI. This may be driven by the law industry suggesting that a relatively small share of legal firms participate in international activities. Knowledge requirements of Medical expertise is a strong negative predictor of future FDI decisions, since this expertise likely requires physical presence (e.g., old peoples homes that belong to the real estate industry).

Again we select the model with the lowest MSPE from the cross-validation and run a Post-LASSO regression. Its results in column 2 of Table 2.3 reveal highly significant correlation of all above mentioned variables (except the Use of software). In stark contrast with the manufacturing sectors, (non-labor) Legal expertise shows strong

Table 2.3: Post-Logit-LASSO Results for Job Tasks

Dep. variable: FDI in 2 years	Post-Logit-LASSO Manufacturing (1)	Services (2)
Job activities:		
Researching, developing	-	12.12***
Teaching, training	3.105	-
Acquiring customers, PR	-	-2.443
Analyzing, investigating	3.136	10.97***
Buying, procurement, selling	-11.76***	-3.082**
Organizing/planning for others	0.353	-0.327
Consulting, informing	-	-2.483**
Measuring, checking	-	2.820*
Negotiating	2.889	2.831*
Serving, caring	-2.377	-
Surveilling, monitoring	-2.095	-4.322**
Repairing	-1.929	-
Producing	-	5.604***
Associated knowledge:		
Management	19.39***	9.080**
Computer engineering	-	-10.54**
Giving presentations	-	1.148
Foreign language	-	-8.301
Legal/law	135.1***	-31.12***
System analysis	1.013	-
Math	-	-4.941*
Other technical knowledge	-	2.431
Labor legislation	88.54	42.12**
Design	-44.82***	-
Use of software	-0.312	0.339
Marketing, sales, PR	-	-
Finance, tax	41.853	-5.075
Native Language (German)	-	-
Labor prot., environm. reg.	2.760	-
Other specialized knowledge	-5.669**	-10.04*
Medical knowledge	-	-20.64***
Non-penalized in LASSO:		
# of establishments	0.516***	0.299***
Employment growth	0.0795**	0.166***
Share of females	1.163***	0.196
(log) wage bill	-0.0070	0.585***
Mean wage growth	0.0353	0.071*
(log) employees	yes	yes
Region FE	yes	yes
Industry FE	yes	yes
Year FE	yes	yes
Observations	57452	51022
$\log \lambda$ of min. MPSE	2.72	2.13

Notes: This table reports the estimated coefficients from a Post-LASSO logit model. The set of included occupational shares is selected by cross-validation finding the model with the lowest MSPE. The MNEs employment size and the industry fixed effects are needed to control for the non-random stratification of non-MNEs. Standard errors are clustered at the treatment level, i.e. firm-level according to Abadie, Athey, et al. 2017. t statistics in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

negative correlations with FDI. Surveilling and monitoring, Consulting, Buying, selling and procurement and Acquiring customers, and Medical and Other specialized

knowledge complete the set of negative predictors we identify. All of these require some kind of geographic proximity (either to the customer or to the local institutions).

We conclude this section by returning to its motivation: to identify tasks that systematically correlate (positively or negatively) with future international activity, whether because they lower the costs of engaging in a FDI à la Helpman, Melitz, and Yeaple 2004, and/or because they increase the benefits of offshoring activities. Overall, many different tasks have predictive power in the service sector and they also feature relatively high levels of statistical significance. In contrast, the best predictive model is much sparser in the manufacturing sector. Within the tasks selected by the LASSO, we find a robust cross-sectoral set of positive predictors such as Management, Labor legislation, and Analyzing/investigating and of negative predictors such as Buying and selling, Surveilling and monitoring, and Special knowledge. Intuitively, the positive predictors are typical of high productive firms and are presumable necessary to engage in international expansion and coordination. Alternatively, more productive firms could also find it profitable both to incur the costs of FDI and the costs of such managerial activities. On the other hand, the identified negative predictors may decrease the benefit-cost ratio of FDI — presumably because the require local networks, interactivity or physical presence and can only be offshored at (prohibitively) high costs — or be characteristic of activities without prospects for market enlargement. Regardless of the implied causality, using the best predicting model for each sector vastly increases the quality of the propensity score matching approach which we describe in the next section.

2.4 FDI and Task Reallocations

The previous results not only have revealed the characteristic task intensities of MNEs relative to non-MNEs, but also provide us with well predicting models of FDI and

their propensity scores (by sector). We now turn to our main analysis and estimate changes in the firms' onshore task demand in response to the FDI.

2.4.1 Empirical Strategy

To weaken potential threats to identification, we control for the selection of firms into treatment status (FDI) on observables by using the propensity scores of the previous section to match each MNE to a similar non-MNE. We then analyze shifts in occupational shares or task intensities using a DiD estimator, and verify that our findings are not driven by any pre-trend.

Propensity-Score Matching

Using propensity scores, we match each MNE to exactly one non-MNE to control for the selection into the FDI status.[28] This step mitigates confounding effects in the DiD-analysis that stem from initial differences in firm characteristics and not causally from the FDI. We thus rely on the identifying assumption that conditional on the matching variables, we compare firms whose decision to engage in FDI activities is tantamount to random.

The choice of matching variables anticipates the predictive power from the economic activity and the other firm characteristics identified in the previous section: firm size in terms of employees, total wage bill, number of plants per firm, the share of female workers, as well as employment and mean wage dynamics (the respective four year log difference), a series of dummies for finer industry classifications, and the set of task intensities identified as predictors in the post-LASSO logit. We capture unobserved heterogeneity from geography by a series of regional dummies of the firm's location.

[28] We have also considered coarsened exact matching as suggested by Iacus, King, and Porro 2012. However, since the LASSO exercise has shown that many different variables are relevant for the prediction of FDI decisions, the coarsened exact matching procedure suffers the curse of dimensionality. It is thus pruning the data excessively, resulting in an insufficient amount of matches.

The matching algorithm is as follows. First, we separate samples for manufacturing and service firms (allowing for a distinction between retail and hospitality on one hand, and transport and business services on the other hand). Using the covariates selected by the LASSO procedure of Section 2.3, we manually select observations whose matching covariates jointly belong to the common support region.[29] Second, we estimate propensity scores using logit models while anticipating the sectoral differences in the selection into FDI. Note that this step is essentially making use of the post-LASSO logit regression from section 2.3, which has reduced the predictive error substantially. Third, we match the MNEs with control firms exactly two years prior to the FDI. This choice includes a trade-off, since the timing of the FDI-effects are heterogeneous: while some firms anticipate the FDI years before they invest and thus adjust their economic behavior accordingly, other firms are little affected until the firm has already invested. Following insights of work by Koerner, Moritz, and Schäffler 2020 analyzing pre- and post-trends in employment between MNEs and non MNEs in the ReLOC data, we choose our exact matching date two years prior to the FDI to avoid confounding effects.[30] In a fourth step, we perform the iterative matching procedure by Borrs and Eppelsheimer 2020, which ensures that treated units are matched to a unique non-MNE with the closest propensity to invest. The algorithm proceeds by first matching the logit propensity scores of MNEs to the three nearest neighboring scores of non-MNEs, and then marking the one with the closest distance.[31] If it is unique, the two firms are matched. If it is not unique (e.g., one non-MNE score is the nearest neighbor for two different MNEs' scores), the algorithm

[29] We thus exclude observations that feature covariates above or below the respective maximum or minimum value of the comparison group $\pm 0.2 \times$standard deviation. The common support region rules out the perfect predictability of FDI from outliers in specific covariates (M. Caliendo and Kopeinig 2008).

[30] Using the same dataset, Koerner, Moritz, and Schäffler 2020 analyze the dynamics of the employment responses of FDI to the Czech Republic. They find in particular that in German MNEs, employment changes initialize within the two years prior to the event.

[31] We apply nearest neighbor matching with replacement and enforce the support region of the logit of the propensity score by caliper width of $0.2 \times$standard deviation (as suggested by Austin 2011b).

compares the distances of these potential matches and selects the smallest one. As a result, some MNEs do not match to the closest non-MNEs: for these firms, the process iterates with marking the non-MNE with the next smallest distance until each MNE is matched to exactly one unique control unit.

The algorithm returns 777 matches (1,554 firms) in the manufacturing sector, and 366 matches (732 firms) in the service sector. As Table B1 reveals, the matching procedure vastly harmonizes firm characteristics within the matches. Compared to the unmatched sample, most of the standardized biases drop from above |0.1| in Table A3 to below |0.05| (a metric suggested by M. Caliendo and Kopeinig 2008 and Austin 2011a). The variance ratios also change from above (resp. below) 2 (0.5) to between 0.700 and 1.3 and are thereby much closer to the ideal of 1. We explain the exceptions from these ranges by the high level of initial heterogeneity in the sample and the high number of matching variables. Table A3 also reveals that untargeted variables from the matching algorithm (Blossfeld occupational groups and number of tasks per worker) also exhibit a decent balancing, with a few exceptions in the service sector (with standardized biases closer to 0.1). Considering the number of variables introduced in our propensity score and the fact that we are not matching neither exactly nor coarsely on any of them, we conclude that our sample balancing is good. [32]

Difference-in-Differences Estimation

We use the matched sample to estimate the MNEs' onshore changes of either occupational shares or task intensities in response to FDI relative to non-MNEs. Let L_{oft} denote the standardized share of occupation or task o in firm f in year t. MNE_f

[32] Further statistics are available in Appendix B, in particular a shift-share decomposition of the firms' workforce around the year of FDI similar to Becker, Ekholm, and Muendler 2013. We are particularly interested in the firm-mix component, which shows, net of aggregate and sector-specific changes, that the employment shift in MNEs between two years prior until four years after the FDI are negative relative to the shifts in non-MNEs.

is an indicator variable for whether firm f engages in FDI to the Czech Republic at time τ during our sample period. For each occupation or task o, we estimate the following model:

$$\begin{aligned} L_{oft} = \quad & \alpha_{PRE}\mathbb{1}\left(t \in [\tau-6;\tau-3]\right) + \beta_{PRE}\mathbb{1}\left(t \in [\tau-6;\tau-3]\right) \times MNE_f \\ & + \alpha_{-1}\mathbb{1}\left(t = \tau-1\right) + \beta_{-1}\mathbb{1}\left(t = \tau-1\right) \times MNE_f \\ & + \alpha_{POST}\mathbb{1}\left(t \in [\tau;\tau+4]\right) + \beta_{POST}\mathbb{1}\left(t \in [\tau;\tau+4]\right) \times MNE_f \\ & + \gamma_f + \delta_t + \varepsilon_{oft}, \end{aligned} \tag{2.4}$$

where the coefficients of interest are β_{POST}. They measure the employment change in MNEs relative to non-MNEs relative to the baseline (omitted) period ($t = \tau - 2$). The coefficients α_{PRE}, and α_{POST} capture trends relative to the baseline period for each year during the observation window from $\tau - 6$ to $\tau + 4$. The parameter δ_t is a time fixed-effect capturing yearly trends. The parameter γ_f denotes firm fixed-effects that capture time-invariant characteristics of the firm. It is needed to compare the changes within MNEs with the changes within non-MNEs. Standard errors ε_{oft} are clustered at the match-level as suggested by Abadie and Spiess 2020.

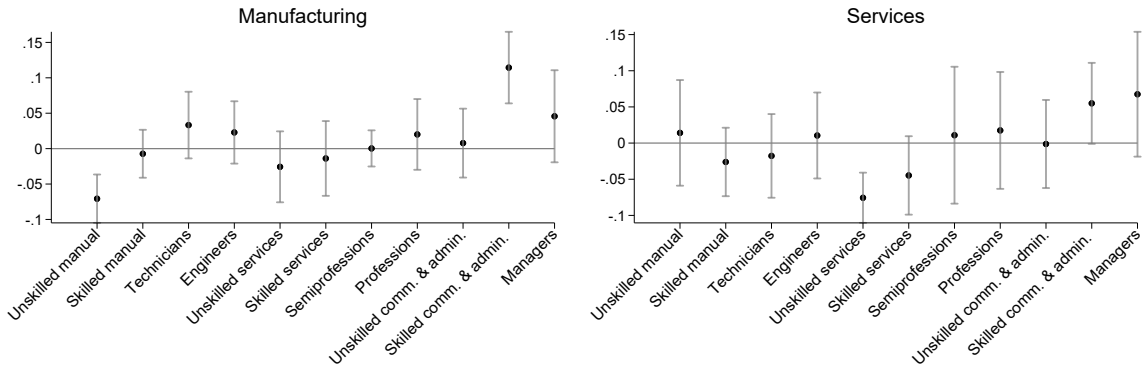
We are particularly interested in the estimates of β_{POST}: a negative estimate would suggest that the occupational share or task intensity o's decrease is stronger in MNEs than in non-MNEs: we label these as FDI-*substitutable*. In contrast, a positive estimate reveals a relative increase of the respective occupational group or task indicating FDI-*complementary* activities.

We also carefully consider the estimates of β_{PRE} to explore potential nonparallel pre-trends between the two groups of firms.[33]

We avoid confounding onshore effects from the anticipation of FDI by a fraction of firms by excluding observations of $\tau - 1$ from the pre-period and post-period

[33]Note that a negative estimate of this coefficient would suggest that MNEs increased their task intensity more than non-MNEs in the pre-period, since it measures relative changes relative to $\tau - 2$.

Figure 2.3: MNEs' Changes in Standardized Occupational Shares relative to non-MNEs



Notes: This figure displays estimated occupational changes in manufacturing (left panel) or service (right panel) MNEs relative to non-MNEs in response to a FDI. Formally it displays the (separately) estimated coefficient β_{POST} from Equation (2.4) where the outcome is the employment share of occupation group o, and associated 95% confidence intervals.

(and treating it as a separate set of coefficients). The results are however robust to including the period $\tau - 1$ in the average post effect.

2.4.2 Results

This section presents the estimates from the matched DiD-model and analyzes shifts in the intensity of either broad occupational categories or specific task contents in response to FDI activities.[34] Due to the standardization of the dependent variables, the estimates are well comparable between groups, regardless of their initial importance in firms.

Broad Occupational Shares

We start with the analysis of occupational shifts. Figure 2.3 presents the matched DiD estimates of β_{POST} from Equation (2.4) and their 95% confidence intervals.

[34] We also show matched DiD estimates of Equation (2.4) at a finer classification of occupations (2-digit) in Appendix C.

In manufacturing MNEs (left panel of Figure 2.3), the FDI affects especially two groups of workers. On the one hand, the shares of Skilled commercial and administrative occupations and of Managers increase relative to non-MNEs, suggesting that these jobs are complementary to offshore production and/or FDI-facilitating. Note that these groups were also identified as the strongest predictors of FDI in Section 2.3.[35] On the other hand, the share of Unskilled manual occupations features the highest downturn relative to non-MNEs. This decrease is in line with previous papers (e.g. Ebenstein et al. 2014; Ottaviano, Peri, and Wright 2013) finding that unskilled manual jobs are the most prone to substitution with low-wage production offshore. Interestingly, Section 2.3 has shown that the share of these jobs has no predictive power on future FDI decisions, implying that prior to the FDI, its direct costs (incl. costs of managers and administrative staff) is the most relevant factor for the investment decision rather than the cost-benefit analysis of substituting manual workers with offshore labor.[36]

In service MNEs (right panel of Figure 2.3), the FDI affects the various occupational shares more heterogeneously. Relative to non-MNEs, we again find positive effects for the shares of Managers and Skilled commercial and administrative occupations. These jobs seem to be the facilitators for the FDI and/or complementary to the activities performed in the Czech affiliates (e.g., organization of multi-site MNEs). We also find negative effects for Unskilled services and a weaker negative effects for Skilled services (significant at the 10% level), which suggests their substitutability with low-wage foreign labor.[37] Strikingly, these groups were identified as negative predictors of FDI in Section 2.3 suggesting here too that cost-benefit con-

[35]Figure C1 in Appendix C reveals that this increase is driven by Managers and Management consultants, as well as Accountants and Data processing or office specialists.

[36]Results for the manufacturing sector are also robust to matching on coarse occupational groups rather than task intensities, but the matching on task intensities is crucial for the service sector.

[37]If they were not offshored, we would have obtained similar negative estimates for all other shares. Figure C2 suggests that surface transport jobs or health occupations are driving this decrease.

siderations of sourcing offshore labor are a subordinate FDI determinant to the costs FDI-facilitating tasks in the firm.

One caveat to the results might be the prevalence of general trends between the MNE and non-MNE groups, because it threatens the validation of our identifying assumption of conditional independence. Specifically, it would imply substantial unobserved heterogeneity between firms that may have explanatory power for FDI and the previous findings. Hence, the existence of any substantial trend would require further assessment of the matching quality.

In order to verify that our results are not driven by initial pre-trends in the variables of interest in MNEs relative to non-MNEs, which would threaten our identifying assumption of conditional independence by implying substantial unobserved heterogeneity between firms that may drive both FDI decisions and employment changes, Figure 2.4 reports the estimates of β_{PRE} from Equation (2.4) and their 95%-interval. Recall that β_{PRE} captures the average deviation in the outcomes of MNEs relative to non-MNEs over the period $\tau - 6$ to $\tau - 3$ relative to $\tau - 2$.

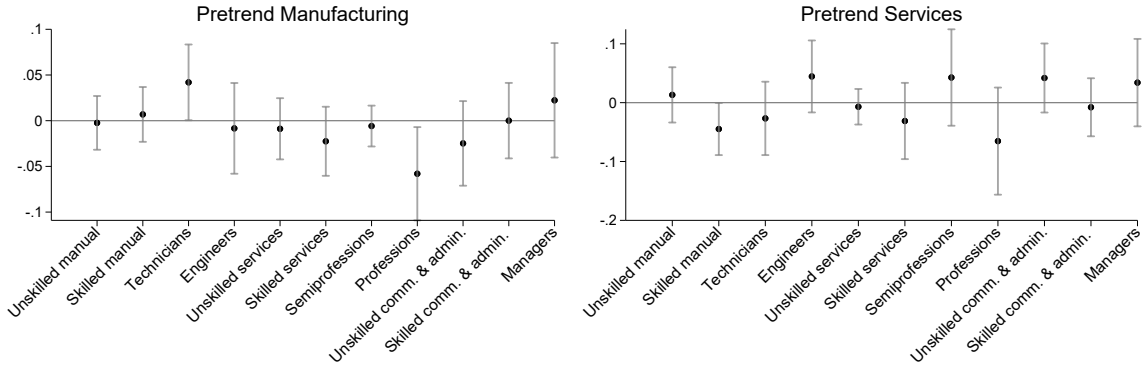
Overall, the figure reveals that our matching does a good job at alleviating risks of unobserved heterogeneity, as most of the estimated coefficients are insignificantly different from zero. This is true in particular for the main groups of interest: Managers, Skilled commercial and administrative occupations, Unskilled manual occupations, Unskilled services and Skilled services (The positive estimates of β_{PRE} for Managers even suggests a relative decrease in MNEs prior to the FDI).[38]

Specific Task Intensities

Turning to the main analysis of interest, we repeat our estimation with tasks intensities, and present estimates of β_{POST} from Equation (2.4) in Figure 2.5 for the

[38] In manufacturing firms we find significant pre-trends for Technicians and Professions. Although these groups have only a small impact on the propensity of FDI (Section 2.3), we cannot completely rule out that another source of firm heterogeneity is driving the effects in the manufacturing sector.

Figure 2.4: Changes in Occupational Shares - Pre-trends verification



Notes: This figure displays estimated employment composition pre-trends in manufacturing (left panel) or service (right panel) MNEs relative to non-MNEs. Formally it displays the (separately) estimated coefficient β_{PRE} from Equation (2.4) where the outcome is the employment share of occupation group o, and associated 95% confidence intervals.

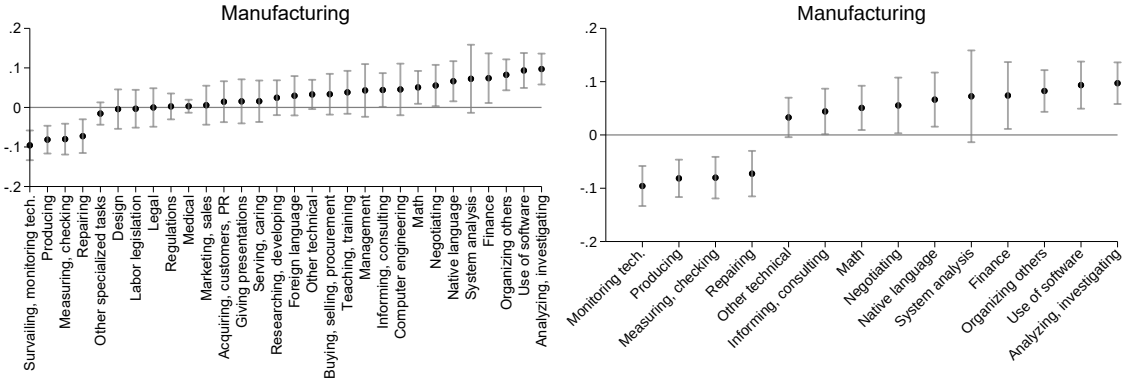
manufacturing sector and in Figure 2.6 for the service sector. Panel (a) of the respective figures shows the results for each task regression, while Panel (b) presents the subset of estimates that are significant at least at a 10% level for the sake of easier interpretation. According to the theory of task trade by Grossman and Rossi-Hansberg 2008, we would expect negative shifts in all tasks with relative offshorablility costs below a certain threshold, and positive or no shifts in the other tasks.[39] Usually, these offshorability costs are measured by codifiability or routineness (e.g., Baumgarten, Geishecker, and Görg 2013; Becker, Ekholm, and Muendler 2013). If we interpret however the ranking of offshorability costs as a ranking of tasks with respect to their wage compensation — instead of any subjective classification — we do find empirical evidence for this phenomenon in the manufacturing MNEs.

Particularly, we find positive shifts in manufacturing firms in favor of organizational tasks and tasks likely pertaining to market analysis: Investigating or analyzing, Organizing the work of others, System analysis, Negotiating. All of these tasks align with the set of FDI-facilitating tasks from Section 2.3, confirming the hypothesis that

[39] Our empirical strategy only allows to identify relative employment changes, whereas the shifts suggested by Grossman and Rossi-Hansberg 2008 are general equilibrium effects. We use their insights to guide our interpretation, while acknowledging the difference.

Figure 2.5: Changes in Standardized Task Intensities - Manufacturing Sector

(a) Full set of separate estimates (b) Changes significant at the 10%-level



Notes: This figure displays estimated task composition changes in manufacturing MNEs relative to non-MNEs in response to a FDI. Formally it displays the (separately) estimated coefficient β_{POST} from Equation (2.4) where the outcome is the intensity of task or knowledge requirement o, and associated 95% confidence intervals. Panel (a) reports the estimates of each regression for task intensity. Panel (b) reports the selected set of estimates significant at the 10% level.

firms face additional challenges in managing and coordinating onshore and offshore activities. Other tasks overlap with typical headquarter activities: Use of software, Finance, Math, or the native language of the parent company (German). We also find positive effects for Management and Training activities, as well as commercial tasks such as Negotiating, Buying, and selling, presumably to cope with a more geographically spread value chain.

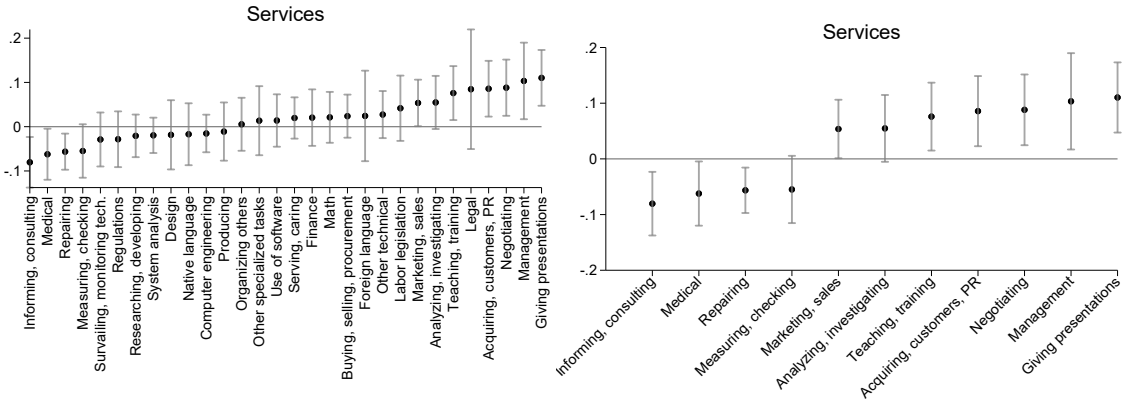
We find negative effects for tasks such as Monitoring, Producing, Checking and measuring, or Repairing. This shift away from production tasks points to efficiency-seeking FDI, where production is relocated to offshore locations. Note also that all of these tasks are low-paid (Table A1) and have been related to routine and/or non-interactive manual work. It suggests that MNEs source relatively simple tasks from their offshore affiliates, and expand their range of well-paid tasks such as management, and sales-related tasks onshore.

In service MNEs, the FDI also increases the intensity of some headquarter tasks such as Management, Training, and Investigating and analyzing. Moreover, we find

Figure 2.6: Changes in Task Intensities - Service sector

(a) Full set of estimates

(b) Selection of significant tasks at the 10%-level



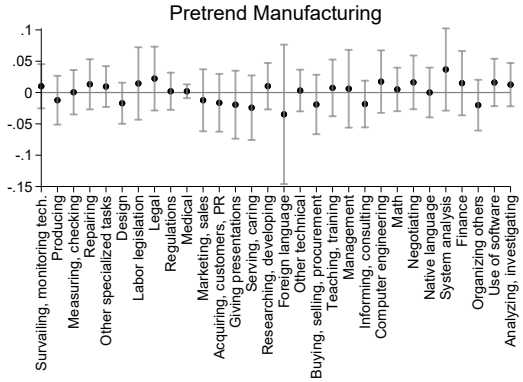
Notes: This figure displays estimated task composition changes in manufacturing MNEs relative to non-MNEs in response to a FDI. Formally it displays the (separately) estimated coefficient β_{POST} from Equation (2.4) where the outcome is the intensity of task or knowledge requirement o, and associated 95% confidence intervals. Panel (a) reports the estimates of each regression for task intensity. Panel (b) reports the selected set of estimates significant at the 10% level.

positive effects for marketing and sales-related tasks such as Giving presentations, Negotiating, and Acquiring customers, Marketing and Public relations. These seem to be complementary to production in offshore affiliates, and are likely to be associated with market-seeking FDI. We also estimate increases in legal activities, which appeared as the best single predictor of future FDI in our analysis of Section 2.3. However, we do not find significant positive effects for some sophisticated tasks that we would expect in a skill-upgrading process such as Maths, Computer Engineering and R&D. On the one hand, this absence may be due to the many MNEs in the low-tech service sector including wholesale, retail, and logistics industries (see Table 2.1). On the other hand, the sample also includes firms in industries such as data-processing, accounting, (technical) consulting, and engineering, that may offshore such activities.[40] This

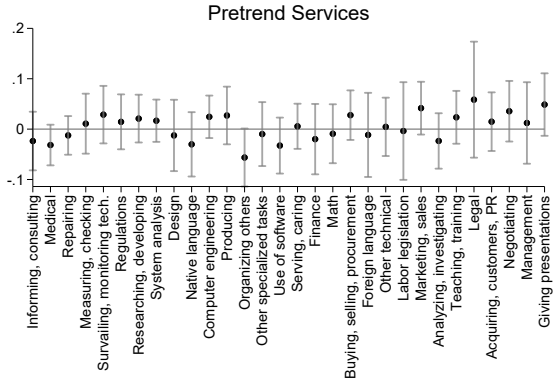
[40]Marin 2004 mentions that many (German) R&D-departments are offshored to Eastern European countries. For example, she explicitly points out that Siemens "plans to centralize and outsource some of its headquarter activities like accounting and management to Siemens subsidiaries in the Czech Republic" (p. 23).

Figure 2.7: Changes in Task Intensities - Pre-trends verification

(a) Manufacturing sector



(b) Service sector



Notes: This figure displays estimated task intensities pre-trends in manufacturing (left panel) or service (right panel) MNEs relative to non-MNEs. Formally it displays the (separately) estimated coefficient β_{PRE} from Equation (2.4) where the outcome is the intensity of task or knowledge requirement o, and associated 95% confidence intervals.

suggests that the matched service firms could still aggregate highly heterogeneous service industries.

We find significant negative estimates for relatively high-skilled service tasks, namely Consulting and informing as well as occupations with a strong Medical knowledge requirements, in line with potential service offshoring. We also obtain negative shifts for production-related tasks: Repairing and Measuring and checking, Monitoring activities and hazardous or polluting tasks associated with the knowledge of respective regulations in Germany. These counter-intuitive results are also in contrast with studies such as Blinder and Krueger 2013, p. 117 who estimate an offshorability share of 1.3% of all workers in "Installation, maintenance, and repair occupations" (using their preferred measure by external coders).[41] We suspect that these negative shifts are driven by a comparative advantage of the Czech Republic in associated economic activities.

[41]Note however that the self-classified share of offshorable workers in this occupation is already about 17-times higher at 22% Blinder and Krueger 2013, p. 117. We refer the reader to Storm 2020 who highlights the advantage of surveyed task measures over classifications by experts.

Figure 2.7 reports the estimates of β_{PRE} from Equation (2.4) and their 95%-interval, in order to assess the existence of pre-trends in specific task intensities prior to the FDI decision. All our estimated pre-trend coefficients are insignificantly different from zero in both sectors, suggesting that our matching is allowing us to indeed compare treated and control unit experiencing the same trajectories prior to the FDI decision. The one notable exception is the intensity of the task Organizing work of others in the service sector, whose estimate is negative and significant at the 10% level. We find no significant effect of the FDI on this task intensity in the post-period, which reassures us that we are not capturing biased effects due to large initial pre-trends.

To conclude this section, our DiD-analysis clearly identifies a set of FDI-complementary tasks whose intensities are expanding significantly in firms opening an affiliate in the Czech Republic relative to non-MNEs. They often pertain to organizational activities, negotiation and analysis, and overlap with tasks identified as positive correlates of future FDI decisions. These positive employment effects are coherent with both a need for stronger coordination across vertically integrated unit, and horizontal expansion of firms to a larger set of markets. We find that negative effects are more heterogeneous across sectors, which may partly stem from a difference of FDI performed (vertical in majority in the manufacturing sector, horizontal in the service sector). The negative estimates from this analysis nonetheless suggest that there are important similarities between FDI- and offshoring-employment effects: both generate negative employment shifts for jobs whose labor can be substituted by low-wage labor in foreign affiliates. We explore how much of this insight we can generalize in the next section.

2.5 FDI, Task Profiles, and Offshorability

Thus far we have identified (sets of) task intensities that either expand, or contract in response to FDI. The literature has attempted to group those occupational task profiles that are affected by international activities (e.g., offshorability, routineness). We examine in this section whether there is an overlap between these groups from earlier studies and the set of tasks that we have identified as FDI-substitutable.

2.5.1 Offshorability Indices

To compare FDI-*substitutable* with offshorable jobs, we borrow established offshorability indices from four sources in the literature, which we report in Table 2.4. The choice of these measures relies on both the intent for the measures' construction (preferably to capture heterogeneous effects of globalization), and the prominence of their use in subsequent studies. For example, Blinder and Krueger 2013 (BK) intended to gauge the potential of service jobs in particular to supply their output to the onshore market while working offshore. Autor, Levy, and Murnane 2003, and the work by Spitz-Oener 2006 (ALM-SO) became the main references for any attempt at quantifying job routineness or codifiability. Their measures (or variants of it) are regularly applied in studies on the substitutability between labor and machines/technology or offshore production. One of these studies is by Becker, Ekholm, and Muendler 2013 (BEM) who develop indices for routine or interactive job profiles using workplace tools in the BiBB Employment Survey. Lastly, Brändle and A. Koch 2017 (BrKo) construct a measure of the offshoring potentials of occupations. Specifically, they conduct a principal component analysis on a battery of tasks in the BiBB Employment Survey that supposedly capture the potential to perform the job abroad. We also add an index that reversely ranks occupations based on the average

educational attainment (skill) of their workers. That is, occupations with the highest shares of low-skilled workers are ranked the highest.

Table 2.4: Selection of Offshorability Indices

Name	Reference	Data source
Offshorability *(Ofty)*	Blinder and Krueger 2013	PDII*
Routine Manual *(RM)*	Autor, Levy, and Murnane 2003 , Spitz-Oener 2006	BiBB 1992, 1998, 2006
Routine non-Analytic *(RnA)*	Autor, Levy, and Murnane 2003 , Spitz-Oener 2006	BiBB 1992, 1998, 2006
Routine non-Interactive *(RnI)*	Autor, Levy, and Murnane 2003 , Spitz-Oener 2006	BiBB 1992, 1998, 2006
Routine tasks *(Rt)*	Becker, Ekholm, and Muendler 2013	BiBB 1998
Non-interactive tasks *(NIt)*	Becker, Ekholm, and Muendler 2013	BiBB 1998
Offshoring Potential *(Off. pot.)*	Brändle and A. Koch 2017	BiBB 1992-2012
Occupational low-skill share	Own	BiBB 1998

Notes: This table displays our choice of established offshorability indices with associated references and its data source. All indices are ordered such that high values imply high offshorability, routineness, high share of low-skilled, etc. For comparison reasons, we also add the Occupatoinal share of low-skilled.
*PDII - Princeton Data Improvement Initiative.

To make the measures comparable, we first adjust the ranking of some of the original measures such that high values of the index (e.g., routine task profile) are always associated with high offshorability.[42] We then take the distribution of each index in a 2% random sample of the universe of employees in Germany and mark the top 25% of these workers as offshorable using a binary variable (based on Baumgarten, Irlacher, and M. Koch 2018 and Blinder and Krueger 2013).[43] While obtaining a well comparable measure across the different indices, our normalization comes at the costs of losing index-dependent thresholds to identify offshorable jobs.

[42]Specifically, this reverses the order of the indices of non-routine or interactive task profiles by BEM, and of non-routine analytic, non-routine interactive jobs by ALM-SO. We therefore rename these indices to routine, non-interactive, routine non-analytic, routine non-interactive.

[43]For a detailed description of the indices replication and normalization, see Appendix D.

Table 2.5: Relative Frequencies of Offshorable Workers across Broad Occupational Groups

	BK	ALM-SO			BEM		BrKo	
	Ofty	RM	RnA	RnI	Rt	NIt	Off. pot.	Low-Skill
Production								
Unskilled manual	15.92	**42.85**	**39.74**	**40.14**	29.48	26.57	12.30	**47.69**
Skilled manual	8.62	**40.10**	2.92	9.11	15.50	11.54	1.64	27.28
Technicians	14.87	0.88	1.41	0.00	0.02	0.71	3.49	0.02
Engineers	7.98	0.00	0.00	0.00	0.16	0.00	0.00	0.00
Services								
Unskilled services	1.66	13.43	**40.08**	**33.19**	**43.48**	14.46	0.00	17.13
Skilled services	1.86	0.08	9.05	9.10	3.54	2.31	0.20	5.10
Semiprofessions	1.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Professions	4.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Administration								
Unskilled commercial and admin.	10.29	0.00	5.08	6.86	3.01	4.75	10.81	2.31
Skilled commercial and admin.	27.91	0.00	0.12	0.00	0.00	**38.38**	**71.58**	0.00
Managers	5.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00

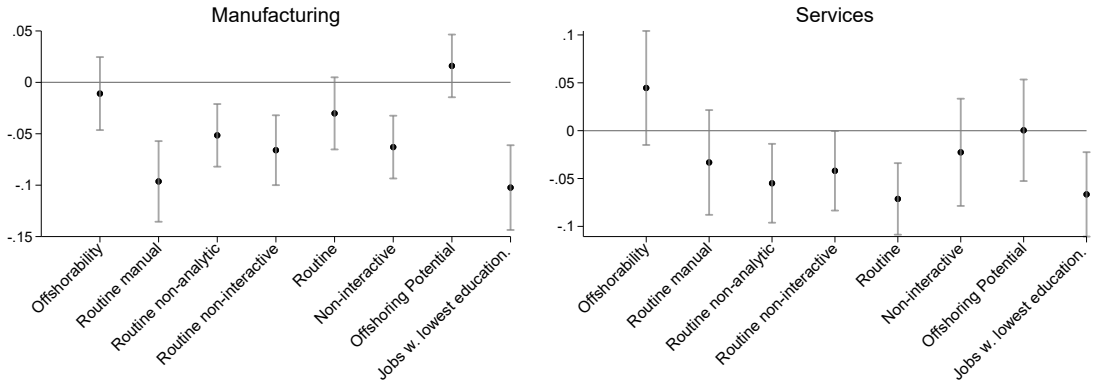
Notes: Relative frequencies of offshorable workers for each measure are taken from a 2% random sample of the universe of employees in Germany. Groups including more than 30% of offshorable workers are marked in bold. We suppress categories of agricultural occupations and workers that cannot be assigned to any occupational category.

Table 2.5 summarizes the outcome of our normalization by displaying the workforce composition in terms of broad occupational groups for each index. While the measure by BK suggests a very differentiated possibility of offshoring jobs across the broad categories (and might suffer due to imprecision of the mapping of American occupational codes to the German classification), ALM-SO's measures identify mainly unskilled manual, unskilled service, or skilled manual jobs. The relative frequencies are similar for the measures by BEM. Skilled commercial and administrative occupations are also considered offshorable by their non-interactive task measure. BrKo expect the latter group as having the highest potential for offshoring. Together with Unskilled commercial and administrative occupations they account for over 80% of the offshorable workers according to their measure. In terms of the lowest average educational attainment, we observe the highest fractions among (unskilled) manual, and unskilled service jobs.

2.5.2 FDI and Shifts in Offshorable Jobs

Due to the similarity between offshoring (in terms of importing inputs) and FDI to a low-wage country (see Antràs and Helpman 2004; Yeaple 2006), we suspect that there is a substantial overlap between offshorable and FDI-substitutable jobs. But before we assess the overlap in the next subsection, we first explore the effects of FDI on offshorable workers and estimate Equation (2.4) using our matched sample and as outcome variables the shares of offshorable workers from the various normalized offshorability measures. Figure 2.8 reports the estimates of β_{POST}.

Figure 2.8: Matched DiD estimation - Standardized Share of Offshorable Workers



Notes: This figure displays estimated changes in employment share of supposedly offshorable jobs in manufacturing (left panel) or service (right panel) MNEs relative to non-MNEs in response to a FDI. Formally it displays the (separately) estimated coefficient β_{POST} from Equation (2.4) where the outcome is the employment share of offshorable workers according to each index of Table 2.4, and associated 95% confidence intervals.

In the manufacturing MNEs, most measures respond to the FDI with a significant decrease in the share of offshorable workers. In particular, the ALM-SO measures imply that offshorable workers are negatively affected by the FDI, whereby the index of routine manual occupations exhibits the largest employment shift. It is similar to the distinction by low educational attainments which underlines the persisting importance of skill levels in explaining the heterogeneity of the labor market effects of globalization. The measures by BK and BrKo do not exhibit a negative effect of FDI

on offshorable workers, who are mainly associated with commercial and administrative occupations that did not experience any drop in response to FDI.[44]

In the service sector, we find fewer or weaker negative effects of FDI on offshorable workers. The highest decreases are featured by routine (BEM), low-skill intensive, or routine and non-analytic jobs (ALM-SO), while, if compared to the manufacturing sector, manual or non-interactive tasks lose importance in identifying the onshore substitution by FDI. The estimate of the BK offshorability measure responds positively to the FDI. This is particularly surprising, since the index is intended to gauge the tradabiliy of tasks in the service sector (considering trade with foreign affiliates *and* offshore outsourcing). We provide two reasons for this deviation to the other measures. First, the BK-measure assigns relatively many administrative occupations as offshorable and this group might react differently to offshore outsourcing than to task trade with foreign affiliates (which demands higher intensities of intra-firm administration). Second, the measure was created for international integration overall and not explicitly for trade between high- and low-wage countries. Their results might therefore capture workforce recomposition effects of FDIs among high-income countries which are much larger in size than between countries at different income levels.[45]

Returning to an overall summary of this exercise, we find that FDI reduces the onshore demand for offshorable workers according to most of the measures. Before drawing stark conclusions about the overlap of FDI-substitutable and offshorable jobs however, we still need to rule out that these results are not merely driven by the normalization of the indices.

[44]It would be interesting for future research to explore whether the drop in this type of labor is absent because FDI to a low-wage country requires more administrative resources than offshore outsourcing.

[45]Koerner 2020 shows that occupations with a complex task profile, as many offshorable occupations identified by the BK index, are more often traded among high-income countries than between high- and low-income countries.

2.5.3 Offshorability Indices and Actual Recomposition

We thus directly compare the already existing ranking of occupations from the established indices to our DiD-findings on the workforce recomposition effects of the FDI. To do so, we first re-run the DiD analysis for fine occupational categories (2-digit occupation codes) and then rank the occupations according to their FDI-substitutability, whereby negative estimates with largest absolute value are ranked the highest (i.e., from 1 decreasing). The explicit estimates are displayed in Figures C1 and C2 in Appendix C. We then directly compare the ranking of FDI-substitutable jobs with the respective ranking of each offshorablity index using Spearman's rank correlation coefficient (to capture any monotone co-movement), on the universe of employees in Germany in 2008 (IAB Employment History - BeH). A high positive correlation implies that the offshorability index ranks similarly offshorable and FDI-substitutable occupations in the context of FDI to a low-wage country. Table 2.6 reports the results.

In the manufacturing sector, the data-driven ranking of jobs correlates positively with most of the indices. The strongest correlation is found with the ranking of routine manual occupations (0.79), which is well in line with our findings in section 2.4 about unskilled manual jobs and (presumably) routine production tasks (Producing, Measuring, Monitoring). This index even adds explanatory power over the measure using the average skill per occupation (0.73). The next highest correlation (0.67) is with the ranking of routine non-interactive jobs and may be driven by the overlap of those manual jobs that also have little face-to-face interaction at their workplace. We find weaker positive correlations with the routine non-analytic index, or the BEM-measures routine, and non-interactive. Notably, the measures by BK and BrKo reveal no or negative correlations with the data-driven ranking.

In the service sector, we generally find weaker correlations between FDI-substitutable occupations and the various offshorability indices. The strongest

Table 2.6: Rank Correlations of Offshorability Indices and FDI-induced Employment Shifts

	Manufacturing	Services
BK		
Offshorability	-0.06	-0.35
ALM-SO		
Routine manual	**0.79**	**0.55**
Routine non-analytic	**0.54**	0.43
Routine non-interactive	**0.67**	**0.64**
BEM		
Routine	**0.63**	0.43
Non-interactive	0.42	0.01
BrKo		
Offshoring potential	-0.21	0.01
By education		
Occupational low skill share	**0.73**	0.45

Notes: This table displays the rank correlations of offshorability indices and actual employment shifts that we obtained from estimating Equation (2.4) per two-digit occupational category. Correlations are computed on the universe of employees in Germany in 2008. Absolute values above 0.5 are marked in bold.

correlation is with ALM-SO measure of routine non-interactive tasks, which — compared with the routine non-analytic index that has a much lower correlation with our data-driven ranking — identifies a larger fraction of skilled manual occupations. We also find a 0.55 correlation with the Routine manual index. The correlation with BK's measure of service offshorability is strongly negative (-0.35). Considering that the measure identifies many sophisticated jobs as offshorable, we interpret this as confirmation that this measure is probably better suited for international integration between high-income countries. Note that these results may otherwise be driven by the larger share of horizontal FDIs relative to traditional vertical FDIs that can be linked to offshoring in this sector.

We conclude this section by an observation: there is a non-negligible overlap between FDI-substitutability and offshorability risk. In the manufacturing sectors,

the overlap is clearly driven by jobs' features of routineness and lack of interactivity. In the service sector, the identification of skilled manual occupations seems crucial to generate a correlation with our data-driven ranking. Indices that aim at capturing offshorability as a sum of these features do not correlate well with FDI-substitutability. We take this exercise as evidence that there is some generalizability of our task level results to a broader set of types of international integration; but also that an analysis at a finer level of task detail may be warranted to unmask heterogeneous effects of trade on onshore employment.

2.6 Conclusion

Although the effects of international activities on onshore labor is a well-studied topic, little is known about the effect of FDI on specific occupations and tasks. In this paper, we have analyzed the effect of FDI to a low-wage country on the onshore task recomposition of a country with substantially higher labor costs.

We first explore potential sources of selection bias of firms into MNE status in terms of workforce composition, using a logit-LASSO regression. We thereby develop a matching procedure that mitigates selection bias otherwise embodied in the DiD. Logit-LASSO models reveal positive correlations of the FDI decisions with high shares of Management and Skilled commercial and administrative occupations, or specific tasks pertaining to the organization and coordination of international activities (headquarter-activities). We interpret these as suggestive evidence that they constitute parts of the fixed costs of FDI as described by Helpman, Melitz, and Yeaple 2004.

Using the propensity scores from the post-LASSO regression, we then match each MNE to a non-MNE and estimate the changes in task intensities between them in response to a FDI decision applying a DiD approach. Our results show that

German manufacturing MNEs expand Skilled commercial and administrative occupations relative to non-MNEs, while Unskilled manual occupations are decreasing. These changes reflect decreases in the intensity of production-related tasks (such as Surveilling and monitoring, Producing, Measuring, and Repairing), and increases in headquarter-activities (such as Analyzing, Organizing others, Use of software, Negotiating, Consulting, the native language of the MNE, Buying, selling and procurement, and System analysis). In service MNEs, we find relative decreases for (Un)skilled services — supposedly the service providers — and relative increases for the share of Managers, and Skilled commercial and administrative occupations. In terms of tasks, we find systematic increases for managerial (Management, Negotiating, Teaching/training others) and marketing tasks (Giving presentations, Public relations). While the management tasks are needed to cope with the fragmented production, marketing tasks may be needed because of higher sales from efficiency gains and/or increased market access. On the negative end of the effects, we do not find systematic decreases in any group of tasks, but rather nuanced decreases of specific intensities of relatively low-wage service providing tasks such as Consulting/informing, Medical knowledge-requiring tasks (e.g., medical laboratories) and Repairing. It is striking that these tasks are explicitly considered non-offshorable by external experts in Blinder and Krueger 2013.

We complete the analysis by drawing a direct link from our outcomes to the literature on offshorable jobs. To do so, we run a similar DiD setup using standardized (2-digit) occupational codes and rank them according to their relative FDI-substitutability. Compared to the occupation ranking from established indices from the literature, we find heterogeneous rank correlations. In the manufacturing sector, indices of routine manual tasks describe well the type of occupations declining in MNEs relative to non-MNEs. In the service sector, we find the strongest effect for routine non-interactive task contents, in line with intuitions provided in the early

offshorability literature (e.g., Blinder 2009). Strikingly, indices that aim at capturing offshorability directly and not via job characteristics (e.g., as routineness) do not correlate well with FDI-substitutability. We interpret this finding as additional motivation for a non-monotone assessment of FDI employment effects on different occupations (as our in our DiD-setup).

Several other aspects are interesting to investigate in further research. After having observed the typical task intensities in firms that invest in a low-wage country and how the tasks intensities change due to this FDI, it would be important to repeat the analysis for FDI to another high-wage country. The composition of FDI (vertical versus horizontal) would potentially be very different. While we could expect to see similar initial intensities in FDI-*facilitating* tasks, we would also expect very different changes of task intensities in response to FDI, due to differences in the comparative advantage of specific (clusters of) tasks as in Grossman and Rossi-Hansberg 2012. Additionally, it would be interesting to explore whether there are substantial differences in initial task intensities between new FDI-engaging firms and incumbent MNEs (e.g., management and HR legal experts could be more intensive in incumbent MNEs, as new MNEs are closer to non-MNEs), and to explore their subsequent reallocation effect (we would expect higher increases in management intensities in new MNEs). Finally, in light of the COVID-19 crisis, we expect relevant avenues for future research in analyzing the comparability of internationally tradable tasks with tasks that can easily be performed from home.

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Appendices

A Additional summary statistics

Categories definitions

Table A1 reports the tasks available in the BiBB 1998 survey, the associated average wages of all workers that perform it, and examples on representative jobs. The best paid task is *Developing and researching*, while *Producing* is the worst paid. Regarding knowledge content, we observe that *Management* skills are at the top of the wage distribution, and that *Other specialized* or *Medical* knowledge are at the bottom. Note that these numbers are derived from the manufacturing and private service sector. The health industry with predominantly public firms is excluded. In the manufacturing sector, 5.32% of the workers perform medical tasks. They are mainly in industries such as manufacture of motor vehicles (25%), (pharmaceuticals, medicinal) chemicals (20%), and manufacture of electrical machinery such as electric motors, generators, and transformers (14%). The majority of these workers are medical receptionists (16%), nursing assistants (15%), physicians (15%), medical lab assistants (12%), or pharmacists (12%). In the service sector, we observe 3.65% of the workers performing medical tasks. They are mainly in the industries "Labour recruitment and provision of personnel" (39%), "Research and experimental development on natural sciences and engineering" (12%), "Wholesale of household goods" (14%) including pharmaceutical and medical goods. The greater share of these workers are social workers (20%), nursing assistants (18%), or medical lab assistants (13%).

Table A2 defines the coarse occupational classification of German jobs according to Blossfeld 1985. Three-digit occupations codes are classified in these groups by typical education level, earnings, and job activities.

Additional summary statistics

Table A3 reports additional summary statistics of the universe of MNEs with affiliates in the Czech Republic and the sample of control firms as refered to in Section 2.2.

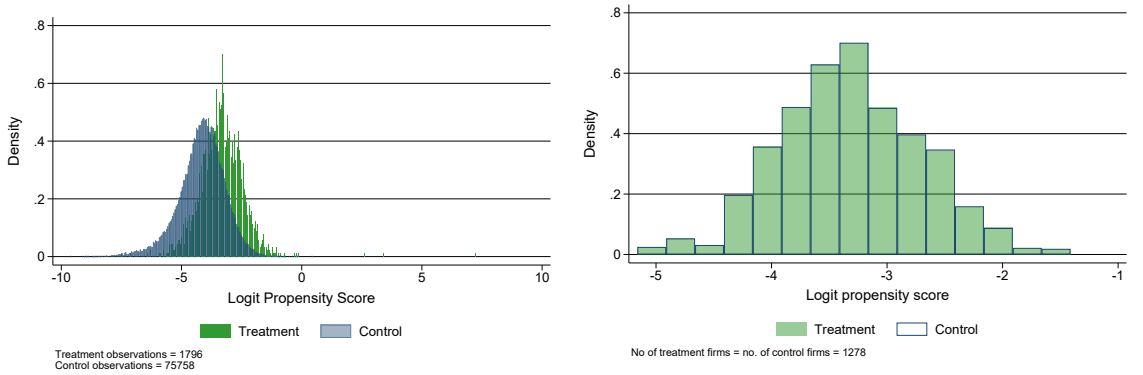
As expected for manufacturing industries, we observe high employment shares in manual occupations that are predominantly unskilled such as assembly workers. Moreover, the MNEs feature a higher share of Skilled commercial and administrative staff (e.g., Accountants) presumably for headquarter activities. In the service sector, (Un)skilled commercial and administrative jobs comprise 40 percent of the median firm's employment (while non-business services represent about 20% of their workforce). The share of Skilled commercial and administrative occupations and of Managers is particularly higher in MNEs relative to non-MNEs.

B Propensity Score Matching

Balancing statistics

Figure B1 illustrates the distribution of propensity scores in treated MNEs (green) and non-MNEs, or control firms (blue). The pre-matching distributions (left) reveal the differences between MNEs and non-MNEs in the propensity to invest in Czech Republic. This difference vastly diminishes after the matching as shown by the almost congruent bars in the right panel.

Figure B1: Distributions of Propensity Scores Pre- and Post-Matching



(a) Full (initial) sample

(b) Matched firms two year prior to (virtual) FDI

Notes: This figure presents the distributions of estimated propensity scores for MNEs (treatment) and non-MNEs (control) of conducting FDI to the Czech Republic in two years. Panel (a) illustrates the distribution before the matching and for all observations of non-MNEs. Panel (b) shows the distribution for matched firms in the year of matching. Propensity scores are derived from a Logit model as described in Section 2.4.1.

In both sectors, the majority of our matching variables do not exceed the thresholds discussed in section 2.4 of $|0.05|$ for the standardized bias, and 1 for the variance ratio. Exceptions in the manufacturing sector are the number of workers, which still vary more across MNEs than non-MNEs, and the service-type occupations. Even after the matching, MNEs employ a high share unskilled service occupations and they feature higher variances for (unskilled) service occupations, and semi-professions. Professions, on the contrary, feature a lower variance in MNEs than in non-MNEs.

Note, however, that service occupations comprise a small share of a firm's workforce. The variances in employment growth or the logarithm of the wage bill also still vary substantially. The matching of firms in the service sectors is preforming similarly well. It however still contains more variation in the composition of the workforce, especially regarding the variance ratios. The greatest differences still persist between employment growth and unskilled commercial and administrative occupations. Taking into account the amount of different and detailed matching variables, we conclude that in overall the resulting sample is much more heterogeneous than before, with firms performing similar sets of tasks or economic activities.

Shift-Share Decomposition of Workforce in the Matched Sample

In this section, we further analyze the matched sample and explore the evolution of employment growth of MNEs relative to non-MNEs around the year of FDI (similarly to Becker, Ekholm, and Muendler 2013). Specifically, this exercise sheds light on whether the FDI was beneficial or detrimental to the relative growth of matched MNEs. We thus decompose gross growth rates and measure the shifts in employment shares between two years prior to the FDI and four years after the FDI. Our metric is the share of employees in the treatment or control firms f that we decompose as follows:

$$\frac{L_{fs}^{t+4} - L_{fs}^{t-2}}{L_{fs}^{t-2}} = \underbrace{\left(\frac{\bar{\bar{L}}^{t+4}}{\bar{\bar{L}}^{t-2}} - 1\right)}_{\text{Aggregate effect}} + \underbrace{\left(\frac{\bar{L}_s^{t+4}}{\bar{L}_s^{t-2}} - \frac{\bar{\bar{L}}^{t+4}}{\bar{\bar{L}}^{t-2}}\right)}_{\text{Sector Mix}} + \underbrace{\left(\frac{L_{fs}^{t+4}}{L_{fs}^{t-2}} - \frac{\bar{L}_s^{t+4}}{\bar{L}_s^{t-2}}\right)}_{\text{Firm Mix}} \tag{2.5}$$

where L_{fs}^t denotes aggregate employment at treatment or control firms f in sector s, $\bar{L}_s^t = \sum_f L_{fs}^t$ is aggregate employment in sector s and $\bar{\bar{L}}^t$ is aggregate employment.

The aggregate effect measures the percentage change in the employment of matched firms and will therefore isolate fluctuations in aggregate labor demand and aggregate labor supply around the identified events. The sector-mix term will

capture deviations in sector-specific employment changes relative to the aggregate employment changes, indicating whether a given sector grows faster or slower than average around the firm specific event. Within sectors, the firm-mix term measures shifts in employment shares across MNEs and non-MNEs relative to the sector-level average.

Table B2 reports the outcomes of the shift-share decomposition of Equation (2.5) both in terms of employment and in terms of tasks. The aggregate effect reveals that the matched firms grew on average by 3.1% in terms of employment and 10.5% in terms of tasks. The high difference in these two measures already points to an upgrading in the complexity of task profile (more tasks per occupation) of the average worker. Similar to other studies (e.g., Autor, Dorn, and Hanson 2013a), we observe decreasing employment in the manufacturing sector (-3.6% by jobs; -3.1% by tasks) relative to aggregate growth. In contrast, we observe increases in the analogue growth measures of the matched service firms (16.6% by jobs; 13.9% by tasks). For our observation period, these numbers are typical for high income countries and have been highlighted before (e.g., Dustmann et al. 2014 for Germany). We now turn to the term of interest, that is, the difference between our FDI-engaging firms and similar domestic players. We start again with the manufacturing sector. FDI-engaging firms decrease in employment size upon opening an affiliate in Czech Republic relative to the sectoral average, by 3% in terms of jobs, and 2.5% in terms of tasks. Control firms on the contrary exceed the sectoral growth by 4.8% in terms of jobs and 4% in terms of tasks over the six-year window. The difference between the MNEs and non-MNEs of up to 8p.p. highlights the substantial role that the FDI played in explaining the downsizing of onshore employment of MNEs. Considering the relative evolution within the service sector, we find that although MNEs are growing slower by 2.4% relative to the sectoral average, they still grow 4.4% faster in terms of the number of tasks they perform onshore. The non-MNEs, in contrast, grow 3.9% faster than the

sectoral average in terms of jobs, but decrease by 7.1% respectively in terms of tasks. Overall, this combination of employment and task growth patterns suggests specialization of the onshore production in manufacturing MNEs and a more complex form of specialization in the service MNEs, where a smaller number of workers performs a wider range of different tasks.

Table A1: Jobs' task and knowledge content

Task content	(Av. daily) Wage *in euros*	Examples
Activities perfomed		
Researching, developing	243.46	Physicists, chemists, mathematicians
Teaching, training	230.79	Scientists, entrepreneurs, managing directors, instructors
Acquiring customers, PR	225.25	Publicity occupations, insurance specialists, commercial artists
Analyzing, investigating	168.21	Data processing specialists, accountants, chemistry and physics technicians
Buying, procurement, selling	160.97	Salespersons, forwarding business dealers, Inn keepers
Organizing/planning others	154.84	Management: consultants, directors, warehouse; specialists: data processing, office; commercial agents; forwarding business dealers; buyers
Consulting, informing	133.79	Specialists: data processing, bank, office; auxiliary office; commercial agents; management consultants
Measuring, checking	131.23	Technicians, assemblers, engineers, warehouse manager
Negotiating	127.86	Buyers; commercial agents; specialists: bank, data-processing, insurance; forwarding business dealers; management; engineers
Serving, caring	119.44	Waiters, telephonists, nursing assistants, nurses
Monitoring, surveilling	106.27	Assistants, assembler, technicians, engineers, nurses, cash collectors, conductors
Repairing	90.56	Chemical plant operatives, driver, precision mechanics, pipe fitters
Producing, manufacturing	73.76	Metal workers, electric motor fitters, carpenters
Associated knowledge		
Management	288.14	Managing directors, management consultants, Engineers
Computer engineering	263.46	Data processing specialists, Electrical engineers
Giving presentation	258.08	Entrepreneurs, commercial agents, vocational advisers
Foreign language	255.19	Air transport occupations, translators, scientists
Legal/law	252.61	Legal representatives, vocational advisers
System analysis	221.72	Data processing specialists
Maths	208.24	Accountants, statisticians, engineers
Other technical knowledge	201.09	Electrical fitters, mechanics, printers
Labor legislation	193.86	HR workers, vocational advisers
Design	175.03	Commercial/graphic artists, Designers
Standard use of software	172.76	Managers, foremen, technicians
Marketing, sales, PR	169.61	Commercial agents, publicity occupations
Finance, tax	142.83	Bank specialists, accountants, tax advisers
German	124.85	Office specialists, journalists, instructors
Regulation (environ., etc.)*	110.43	Chemical plant operatives, tracklayers, generators machinists
Other specialized knowledge	90.77	Food processors, scientific specialists, (telecommunications, chemical, ...) technical specialists
Medical knowledge	87.65	Social workers, nursing assistants, nurses, medical receptionists, medical lab assistants

Notes: This table describes jobs' activities and specific knowledge requirements for a given job as available in the BiBB Employment Survey of 1998. Daily wages are drawn from a cross section in 2010. Task intensity is the frequency of a given task or knowledge requirement divided by the total number of tasks performed in the firm two years prior to the FDI. PR stands for "public relations". Note that most occupations are associated with more than one task, so that the total number of tasks may exceed the total number of employees. *The task regulation includes knowledge requirements on rules for labor protection such as accident prevention, safety regulations, occupational health and safety, as well as environmental regulations.

Table A2: Coarse Occupational Classification (Blossfeld)

Coarse occupational category	Wage	Examples
Production		
Unskilled manual occupations (UMO)	68.55	Assembly, conveyors, and riveter workers, roadmaker
Skilled manual occupations (SMO)	84.81	Electricians, mechanics, carpenters, lab assistant, vehicle repairers, carpenters
Technicians (TEC)	151.02	Mechanical engineer, surveying technicians
Engineers (ENG)	279.74	Architect, (electro-, ...)engineers, chemists
Service		
Unskilled service occupations (USO)	58.67	Janitors, waiters, receptionists, conductors, warehouse managers, packers, cleaners
Skilled service occupations (SSO)	93.32	Train drivers, hairdressers, pharmacy chemists, judicial officers, administr. and enforcers, medical receptionists, pharmaceutical assistants, property managers, safety testers
Semi-professions (SEMI)	127.77	Nurses, social workers, teachers, journalists, translators, archivists
Professions (PROF)	223.31	Doctors, (economic and social) scientists, professors, legal consultants, statisticians
Administration		
Unskilled commercial and admin. (UCA)	73.95	Cashiers, auxiliary office (secretaries), auxiliary commercial agents (buyer, seller)
Skilled commercial and admin. (SCA)	131.91	Bankers, accountants; forwarding, logistics specialists; wholesale traders, data processing, office specialists
Managers (MAN)	277.71	CEOs, business owners, high-level public servants

Notes: This table describes broad occupational classification by Blossfeld 1985. Each group represents a socio-economic strata of the German workforce by similar education-levels, average earnings, as well as types of activities performed. Daily wages are drawn from a cross section in 2010.

Table A3: Summary Statistics - Unmatched Sample

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Plants per firm	2.256	1.594	0.179	11.70	3.093	0.060
	1	*1*	.	*1*	*1*	.
	(4.397)	(2.853)	(2.375)	(203.7)	(12.73)	(255.9)
Size (employees)	814.8	222.2	0.139	443.5	143.0	0.080
	139	*147*	.	*32*	*49*	.
	(6032.7)	(335.8)	(322.8)	(5270.3)	(489.0)	(116.2)
(Daily) wage bill	98.791	24.585	0.137	46.865	13.754	0.096
(in thousand euros)	*13.431*	*13.049*	.	*36.517*	*41.608*	.
	(761.538)	(60.113)	(160.5)	(484.139)	(48.973)	(97.73)
Number of tasks	21.46	20.26	0.211	16.14	14.97	0.180
	23	*22*	.	*17*	*15*	.
	(5.638)	(5.672)	(0.988)	(6.756)	(6.261)	(1.165)
Tasks per worker	5.144	4.853	0.215	5.499	4.890	0.250
	5.081	*4.816*	.	*5.500*	*4.635*	.
	(1.316)	(1.384)	(0.904)	(2.263)	(2.603)	(0.756)
Broad occupations shares (%)						
Production						
Unskilled manual	36.45	32.12	0.171	5.050	5.337	-0.0194
	37.30	*30.08*	.	*0*	*0*	.
	(25.26)	(25.49)	(0.982)	(14.35)	(15.20)	(0.891)
Skilled manual	19.70	25.53	-0.276	5.031	7.766	-0.180
	13.41	*19.21*	.	*0*	*0*	.
	(19.59)	(22.58)	(0.753)	(13.19)	(16.91)	(0.608)
Technicians	8.835	7.756	0.104	4.935	4.051	0.0706
	6.885	*5.263*	.	*0*	*0*	.
	(9.912)	(10.87)	(0.831)	(12.37)	(12.67)	(0.953)
Engineers	3.716	2.853	0.137	4.225	2.825	0.118
	1.681	*0.611*	.	*0*	*0*	.
	(6.306)	(6.317)	(0.996)	(12.64)	(10.96)	(1.329)
Services						
Unskilled service	6.048	7.129	-0.116	16.89	24.67	-0.268
	4.100	*4.244*	.	*3.846*	*8.861*	.
	(7.722)	(10.71)	(0.520)	(25.58)	(32.06)	(0.636)
Continued below						

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Skilled service	0.341	0.504	-0.0591	0.818	1.801	-0.142
	0	*0*	.	*0*	*0*	.
	(2.484)	(3.000)	(0.686)	(4.683)	(8.640)	(0.294)
Semi-professions	0.201	0.401	-0.0853	0.497	0.315	0.0492
	0	*0*	.	*0*	*0*	.
	(1.508)	(2.940)	(0.263)	(4.126)	(3.209)	(1.653)
Professions	0.328	0.240	0.0529	0.808	0.847	-0.00791
	0	*0*	.	*0*	*0*	.
	(1.459)	(1.842)	(0.628)	(4.868)	(5.182)	(0.883)
Administration						
Unskilled commercial and admin.	3.763	6.559	-0.242	11.06	12.96	-0.0890
	1.626	*1.429*	.	*2.439*	*1.961*	.
	(7.080)	(14.72)	(0.231)	(19.70)	(22.86)	(0.743)
Skilled commercial and admin.	17.45	14.57	0.219	43.17	34.23	0.285
	14.29	*12*	.	*38.46*	*23.81*	.
	(13.56)	(12.60)	(1.157)	(30.84)	(31.96)	(0.931)
Managers	2.999	2.203	0.155	7.281	4.782	0.177
	1.660	*1.214*	.	*1.961*	*0.410*	.
	(5.712)	(4.457)	(1.642)	(15.32)	(12.86)	(1.418)
Activities performed						
Researching, developing	1.198	0.963	0.185	1.174	0.723	0.222
	0.842	*0.556*	.	*0*	*0*	.
	(1.317)	(1.223)	(1.159)	(2.202)	(1.838)	(1.435)
Teaching, training	1.878	1.550	0.223	2.442	2.206	0.080
	1.644	*1.299*	.	*1.429*	*0.769*	.
	(1.476)	(1.456)	(1.028)	(2.790)	(3.092)	(0.814)
Acquiring customers, PR	0.998	0.942	0.041	1.958	1.520	0.175
	0.582	*0.451*	.	*0.986*	*0.465*	.
	(1.287)	(1.478)	(0.758)	(2.581)	(2.439)	(1.120)
Analyzing, investigating	7.166	6.201	0.273	12.03	10.18	0.380
	6.874	*5.818*	.	*12.50*	*10.34*	.
	(3.500)	(3.571)	(0.960)	(4.506)	(5.191)	(0.753)

Continued below

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Buying, selling	1.908	2.790	-0.256	4.689	5.618	-0.146
	1.540	*1.365*	.	*3.286*	*2.852*	.
	(1.763)	(4.547)	(0.150)	(5.157)	(7.407)	(0.485)
Organizing others	9.328	8.523	0.207	13.24	11.80	0.300
	9.414	*8.551*	.	*13.64*	*11.84*	.
	(3.684)	(4.070)	(0.819)	(4.420)	(5.157)	(0.735)
Consulting, informing	13.43	14.00	-0.128	15.23	16.93	-0.232
	13.45	*13.83*	.	*15.13*	*15.85*	.
	(3.874)	(4.930)	(0.618)	(5.017)	(9.057)	(0.307)
Measuring, checking	13.51	13.58	-0.0133	5.437	5.617	-0.033
	13.56	*13.82*	.	*4.255*	*4.206*	.
	(5.473)	(5.471)	(1.000)	(5.321)	(5.744)	(0.858)
Negotiating	3.156	2.792	0.178	5.504	4.772	0.187
	3.086	*2.500*	.	*5.508*	*4.094*	.
	(1.956)	(2.145)	(0.832)	(3.811)	(4.019)	(0.899)
Serving, caring	1.641	2.613	-0.279	3.834	5.973	-0.326
	1.334	*1.199*	.	*2*	*2.958*	.
	(1.729)	(4.618)	(0.140)	(5.219)	(7.661)	(0.464)
Monitoring, surveilling	11.84	12.41	-0.095	2.808	3.796	-0.168
	11.91	*12.50*	.	*0.358*	*0.416*	.
	(5.906)	(6.098)	(0.938)	(5.053)	(6.584)	(0.589)
Repairing	8.015	8.612	-0.103	6.183	6.838	-0.042
	7.565	*8.303*	.	*0.308*	*0.635*	.
	(5.500)	(6.060)	(0.824)	(15.88)	(15.21)	(1.089)
Manufacturing	8.879	9.533	-0.102	1.300	1.805	-0.110
	8.434	*9.259*	.	*0*	*0*	.
	(6.373)	(6.448)	(0.977)	(3.893)	(5.192)	(0.562)
Associated knowledge						
Management	0.539	0.432	0.152	0.965	0.631	0.231
	0.339	*0.264*	.	*0.342*	*0*	.
	(0.762)	(0.635)	(1.443)	(1.629)	(1.249)	(1.702)

Continued below

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Computer engineering	0.376 *0.151* (0.689)	0.275 *0.053* (0.591)	0.158 . (1.355)	0.698 *0* (1.757)	0.419 *0* (1.425)	0.174 . (1.520)
Giving presentations	0.841 *0.435* (1.115)	0.734 *0.350* (1.160)	0.0943 . (0.925)	1.471 *0.662* (2.133)	0.990 *0.158* (1.768)	0.245 . (1.456)
Foreign language	0.062 *0* (0.226)	0.046 *0* (0.235)	0.066 . (0.924)	0.031 *0* (0.178)	0.044 *0* (0.548)	-0.033 . (0.105)
Legal / Law	0.018 *0* (0.132)	0.008 *0* (0.041)	0.097 . (10.40)	0.017 *0* (0.115)	0.032 *0* (0.378)	-0.054 . (0.092)
System analysis	0.204 *0.066* (0.452)	0.161 *0* (0.384)	0.101 . (1.390)	0.601 *0* (1.685)	0.368 *0* (1.358)	0.153 . (1.540)
Maths	1.431 *1.155* (1.336)	1.186 *0.804* (1.417)	0.178 . (0.890)	1.462 *0.357* (2.470)	2.009 *0.263* (3.520)	-0.180 . (0.492)
Other technical	1.584 *0.881* (2.036)	1.445 *0.709* (2.048)	0.0683 . (0.988)	0.750 *0* (1.810)	0.597 *0* (1.668)	0.088 . (1.177)
Labor legislation	0.008 *0* (0.027)	0.006 *0* (0.022)	0.086 . (1.420)	0.006 *0* (0.093)	0.005 *0* (0.110)	0.012 . (0.705)
Design	0.069 *0* (0.404)	0.215 *0* (1.051)	-0.182 . (0.148)	0.0904 *0* (0.549)	0.101 *0* (0.658)	-0.018 . (0.696)
Use of software	6.453 *5.988* (4.413)	5.373 *5.089* (3.174)	0.281 . (1.933)	10.30 *10.34* (4.994)	8.725 *8.929* (5.728)	0.292 . (0.760)

Continued below

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Marketing, sales	0.335	0.293	0.051	0.615	0.423	0.125
	0	*0*	.	*0*	*0*	.
	(0.795)	(0.841)	(0.894)	(1.685)	(1.372)	(1.508)
Finance, taxes	0.203	0.186	0.034	0.554	1.242	-0.285
	0.057	*0.044*	.	*0*	*0*	.
	(0.465)	(0.527)	(0.779)	(1.606)	(3.015)	(0.284)
Native language (German)	3.111	2.713	0.142	5.950	5.440	0.094
	2.361	*2.007*	.	*4.376*	*3.704*	.
	(2.876)	(2.756)	(1.089)	(5.435)	(5.407)	(1.011)
Regulations*	1.198	1.093	0.048	0.354	0.487	-0.073
	0.424	*0.277*	.	*0*	*0*	.
	(2.185)	(2.224)	(0.965)	(1.402)	(2.163)	(0.420)
Other specialized	0.546	1.203	-0.258	0.275	0.552	-0.140
	0	*0*	.	*0*	*0*	.
	(1.895)	(3.053)	(0.385)	(1.730)	(2.191)	(0.624)
Medical knowledge	0.074	0.121	-0.047	0.038	0.155	-0.131
	0	*0*	.	*0*	*0*	.
	(0.865)	(1.081)	(0.639)	(0.337)	(1.216)	(0.077)

End of table

Notes: Table A3 describes the summary statistics for 971 (863) MNEs in the manufacturing (service) sector two years prior to the FDI and the respective statistics of 3,320 (3,860) manufacturing (service) non-MNEs across all years. For each variable, we report the mean, median and standard deviation. In comparing MNEs and non-MNEs, we also report the standardized bias and the variance ratio between the two groups. The wage bill is denoted in 2010-constant euros. Employment and wage growth are measured as the four-year log difference. *The task *Regulations* includes knowledge requirements on rules for labor protection, such as accident prevention, safety regulations, occupational health and safety, as well as environmental regulations.

Table B1: Summary Statistics - Matched Sample

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
(Log) Plants per firm	0.309	0.309	0.001	0.464	0.429	0.044
	0	*0*	.	*0*	*0*	.
	(0.540)	(0.549)	(0.968)	(0.850)	(0.741)	(1.313)
(Log) Size (employees)	4.895	4.908	-0.009	3.688	3.487	0.122
	4.942	*5.159*	.	*3.714*	*3.526*	.
	(1.525)	(1.332)	(1.310)	(1.712)	(1.603)	(1.140)
(Log) Wage bill (in euros)	9.415	9.441	-0.017	8.392	8.166	0.127
	9.487	*9.638*	.	*8.486*	*8.194*	.
	(1.644)	(1.444)	(1.296)	(1.832)	(1.721)	(1.133)
Employment growth	3.064	3.123	-0.055	2.841	2.763	0.069
	2.833	*2.891*	.	*2.736*	*2.721*	.
	(1.187)	(0.954)	(1.548)	(1.224)	(1.031)	(1.410)
Wage growth	2.093	2.071	0.025	2.436	2.416	0.022
	2.161	*2.140*	.	*2.257*	*2.257*	.
	(0.881)	(0.851)	(1.072)	(0.938)	(0.880)	(1.135)
Female employees (percent)	32.56	32.45	0.005	39.83	40.93	-0.046
	27.12	*27.71*	.	*36.38*	*36.36*	.
	(21.05)	(21.21)	(0.985)	(23.22)	(24.91)	(0.869)
Task intensities (percent)						
Activities performed						
Researching, developing	1.188	1.250	-0.047	1.274	1.356	-0.035
	0.837	*0.840*	.	*0.176*	*0*	.
	(1.301)	(1.379)	(0.890)	(2.295)	(2.373)	(0.935)
Teaching, training	1.858	1.803	0.040	2.400	2.542	-0.053
	1.610	*1.593*	.	*1.491*	*1.516*	.
	(1.449)	(1.345)	(1.162)	(2.567)	(2.759)	(0.866)
Acquiring customers, PR	0.961	0.905	0.046	1.971	2.020	-0.020
	0.565	*0.492*	.	*1.116*	*1.186*	.
	(1.214)	(1.235)	(0.967)	(2.458)	(2.451)	(1.006)
Analyzing, investigating	7.028	7.028	0	12.51	12.39	0.030
	6.778	*6.443*	.	*12.84*	*12.50*	.
	(3.311)	(3.396)	(0.951)	(3.839)	(3.878)	(0.980)

Continued below

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Buying, selling, procurement	1.832	1.747	0.053	4.451	4.700	-0.058
	1.475	*1.267*	.	*3.448*	*3.659*	.
	(1.552)	(1.658)	(0.876)	(4.286)	(4.345)	(0.973)
Organizing others	9.292	9.185	0.031	13.55	13.46	0.024
	9.401	*8.992*	.	*13.87*	*13.35*	.
	(3.609)	(3.340)	(1.168)	(3.859)	(3.927)	(0.966)
Informing, consulting	13.46	13.44	0.007	14.79	14.83	-0.010
	13.54	*13.48*	.	*15.02*	*15.15*	.
	(3.692)	(3.838)	0.925	(4.108)	(3.972)	(1.069)
Measuring, checking	13.72	13.90	-0.035	5.137	5.054	0.019
	13.63	*13.96*	.	*4.208*	*4.632*	.
	(5.283)	(5.135)	(1.059)	(4.532)	(4.189)	(1.170)
Negotiating	3.083	3.054	0.016	5.791	6.041	-0.071
	2.970	*2.803*	.	*5.687*	*6.208*	.
	(1.863)	(1.926)	(0.936)	(3.509)	(3.553)	(0.975)
Serving, caring	1.581	1.475	0.075	3.355	3.497	-0.034
	1.314	*1.168*	.	*1.983*	*2.060*	.
	(1.514)	(1.340)	(1.276)	(4.243)	(4.069)	(1.087)
Surveilling, monitoring	12.04	12.09	-0.009	2.484	2.440	0.010
	12	*12.30*	.	*0.440*	*0.349*	.
	(5.630)	(5.379)	(1.095)	(4.466)	(4.391)	(1.034)
Repairing	8.259	8.324	-0.013	6.314	5.586	0.050
	7.924	*8.113*	.	*0.563*	*0.540*	.
	(5.309)	(4.823)	(1.212)	(15.35)	(13.85)	(1.229)
Producing, manufacturing	9.063	9.201	-0.025	1.388	1.288	0.025
	8.679	*8.873*	.	*0*	*0*	.
	(6.237)	(6.031)	(1.070)	(4.123)	(3.752)	(1.208)
Associated knowledge						
Management	0.515	0.479	0.055	0.906	0.921	-0.011
	0.332	*0.324*	.	*0.415*	*0.360*	.
	(0.712)	(0.593)	(1.440)	(1.376)	(1.368)	(1.012)

Continued below

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Computer engineering	0.359 *0.145* (0.647)	0.366 *0.135* (0.711)	-0.010 . (0.827)	0.837 *0* (1.953)	0.881 *0* (2.029)	-0.022 . (0.927)
Giving presentations	0.831 *0.434* (1.107)	0.752 *0.419* (1.058)	0.073 . (1.094)	1.408 *0.752* (1.862)	1.524 *0.841* (1.986)	-0.060 . (0.879)
Foreign language	0.054 *0* (0.187)	0.061 *0* (0.228)	-0.034 . (0.675)	0.025 *0* (0.124)	0.033 *0* (0.189)	-0.046 . (0.435)
Legal / Law	0.008 *0* (0.027)	0.010 *0* (0.034)	-0.041 . (0.615)	0.013 *0* (0.069)	0.011 *0* (0.078)	0.024 . (0.767)
System analysis	0.188 *0.060* (0.420)	0.210 *0.069* (0.511)	-0.047 . (0.675)	0.757 *0* (1.913)	0.741 *0* (1.917)	0.008 . (0.996)
Maths	1.419 *1.158* (1.293)	1.492 *1.109* (1.512)	-0.052 . (0.731)	1.388 *0.518* (2.241)	1.642 *0.456* (2.675)	-0.103 . (0.702)
Other technical	1.612 *0.879* (2.051)	1.630 *0.931* (2.011)	-0.009 . (1.040)	0.638 *0* (1.536)	0.772 *0* (1.725)	-0.082 . (0.793)
Labor legislation	0.006 *0* (0.018)	0.007 *0* (0.022)	-0.066 . (0.670)	0.001 *0* (0.007)	0.0045 *0* (0.052)	-0.099 . (0.019)
Design	0.052 *0* (0.266)	0.056 *0* (0.274)	-0.013 . (0.943)	0.089 *0* (0.533)	0.117 *0* (0.681)	-0.045 . (0.612)
Use of software	6.206 *5.930* (3.044)	6.251 *5.748* (3.108)	-0.014 . (0.959)	10.73 *10.61* (4.430)	10.59 *10.51* (4.617)	0.032 . (0.920)

Continued below

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Marketing, sales	0.339	0.303	0.044	0.653	0.643	0.006
	0	*0*	.	*0*	*0*	.
	(0.828)	(0.836)	(0.981)	(1.671)	(1.575)	(1.126)
Finance, taxes	0.184	0.193	-0.022	0.522	0.653	-0.080
	0.061	*0.079*	.	*0*	*0*	.
	(0.331)	(0.494)	(0.451)	(1.370)	(1.861)	(0.542)
Native language (German)	2.982	2.976	0.002	6.132	5.830	0.058
	2.313	*2.237*	.	*4.969*	*4.186*	.
	(2.574)	(2.796)	(0.848)	(5.037)	(5.295)	(0.905)
Regulations	1.289	1.325	-0.016	0.348	0.287	0.051
	0.437	*0.471*	.	*0*	*0*	.
	(2.262)	(2.281)	(0.984)	(1.230)	(1.155)	(1.134)
Other specialized	0.511	0.452	0.037	0.110	0.120	-0.016
	0	*0*	.	*0*	*0*	.
	(1.760)	(1.447)	(1.480)	(0.603)	(0.617)	(0.953)
Medical	0.073	0.038	0.052	0.027	0.026	0.005
	0	*0*	.	*0*	*0*	.
	(0.881)	(0.369)	(5.716)	(0.172)	(0.387)	(0.197)
Untargeted variables						
Tasks per worker	5.145	5.092	0.042	5.457	5.490	-0.014
	5.119	5.024	.	5.491	5.333	.
	1.227	1.300	0.891	2.207	2.410	0.839
[0.3 em] Number of different tasks	21.54	21.70	-0.033	17.02	16.22	0.134
	22	23	.	18	17	.
	5.251	4.822	1.186	6.143	5.892	1.087
Broad occupational categories (shares)						
Production						
Unqual. manual occ.	37.06	35.64	0.057	4.801	4.923	-0.009
	37.96	35.46	.	0	0	.
	24.98	24.44	1.044	13.27	14.28	0.864
Continued below						

	Manufacturing			Service		
	MNEs	non-MNEs	Balancing	MNEs	non-MNEs	Balancing
	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)	Mean *Median* (Std. dev.)	Mean *Median* (Std. dev.)	Std. bias (Var. ratio)
Qual. manual occ.	20.13	21.87	-0.090	3.794	3.435	0.035
	14.29	16.89	.	0	0	.
	19.39	19.43	0.996	10.20	10.17	1.005
Technicians	9.088	9.228	-0.014	5.632	4.604	0.085
	7.105	7.216	.	0	0	.
	9.767	9.848	0.984	13.20	10.78	1.498
Engineers	3.501	3.688	-0.031	3.721	5.224	-0.114
	1.739	1.462	.	0	0	.
	5.275	6.703	0.619	10.95	15.00	0.533
Services						
Unqual. service occ.	6.240	6.222	0.002	18.13	19.67	-0.058
	4.054	4.138	.	5.302	5.463	.
	8.357	9.038	0.855	25.57	27.15	0.887
Qual. service occ.	0.243	0.511	-0.120	0.638	1.269	-0.132
	0	0	.	0	0	.
	1.142	2.953	0.150	2.502	6.289	0.158
Semiprof.	0.154	0.123	0.031	0.239	0.247	-0.004
	0	0	.	0	0	.
	1.042	0.902	1.335	1.688	1.978	0.728
Professions	0.255	0.300	-0.039	0.799	0.849	-0.013
	0	0	.	0	0	.
	0.814	1.413	0.332	3.817	3.566	1.146
Administration						
Unqual. admin. occ.	3.538	3.478	0.0102	9.993	9.271	0.045
	1.639	1.566	.	3.125	3.120	.
	5.795	6.125	0.895	16.96	14.80	1.314
Qual. admin. occ.	16.94	16.17	0.061	46.10	43.17	0.101
	14.25	13.18	.	42.60	40.48	.
	12.40	12.89	0.925	29.03	28.93	1.007
Managers	2.812	2.695	0.022	5.891	7.254	-0.110
	1.660	1.515	.	2.395	2.159	.
	5.008	5.658	0.783	10.76	13.86	0.602
End of table						

Notes: Table B1 describes the summary statistics for 738 (540) MNEs in the manufacturing (service) sector and their matched non-MNEs two years prior to the FDI. For each variable, we report the mean, median and standard deviation. In comparing MNEs and non-MNEs, we also report the standardized bias and the variance ratio between the two groups. The wage bill is denoted in 2010-constant euros. Employment or wage growth is measured as the log difference between $t-2$ and $t-6$.

Table B2: Shift-Share Decomposition of Matched Sample

	MNEs	non-MNEs
Aggregate labor supply change		
Employment shift	0.0313	
Tasks shift	0.1045	
Manufacturing		
Between-sectors employment shift (net of aggregate)	-0.0361	
Between-sectors tasks shift (net of aggregate)	-0.0312	
Within-sector between-firms employment reallocation	-0.0290	0.0475
Within-sector between-firms tasks reallocation	-0.0252	0.0404
Services		
Between-sectors employment shift (net of aggregate)	0.1657	
Between-sectors tasks shift (net of aggregate)	0.1386	
Within-sector between-firms employment reallocation	-0.0243	0.0391
Within-sector between-firms tasks reallocation	0.0439	-0.0706

Notes: This table reports outcomes of the shift-share decomposition in Equation (2.5). It starts with the aggregate changes of all matched firms in terms of employment and tasks performed. The between-sector panel reports Manufacturing- or Service-specific employment shift relative to aggregate labor changes and the within-sector panel reports the firm-mix term for treated and control firms separately.

C Finer Occupational Categories

In this appendix, we repeat the analyses of Sections 2.3 and 2.4 for 93 occupational categories (two-digit *KldB88*) for two reasons: first, it allows us to underpin our conjectures with detailed occupational information. Besides the occupational groups and detailed tasks, we will also know about the finer job categories. Second, the very disaggregated unit of analysis enables us to relate the matched DiD outcomes with offshorability indices in Section 2.5. The analysis of very disaggregated units, however, also has its drawback. The lower the number of observations per occupation, the more variance the estimates contain and the more inaccurate the estimates become. This is why we proceeds with more broader classifications in the main text.

LASSO-Logit Regression

In this section, we explore which job titles feature high predictive power to predict a firm's propensity to conduct FDI two years later. The reasoning behind this inspection is the conjecture that firms with a high share of either substitutable or complementary workers benefit disproportionately from offshore expansions. On the one hand, because the costs of FDI could be better compensated by subsequent benefits from labor cost savings in firms with a high share of substitutable jobs. On the other hand, because complementary jobs could lower the relative costs of opening a foreign affiliate, since for example, the firm does not need to hire additional workers to cope with the extra costs of international coordination. The methodological setup is similar to our logit-LASSO regression of Equation (2.3), where we use the employment shares of 93 occupation titles in the vector τ_{ft}.

Due to the multiplicity of groups, we do not show the coefficients' path along the values of λ (as in Figures 2.1 and 2.2). Instead, we show the post-LASSO logit results. Table C1 reports this outcomes for the manufacturing and service sector.

Table C1: Post-LASSO Logit Results for Occupation Titles

	Post-Logit-LASSO	
Dep. variable: FDI in 2 years	Manufacturing	Services
	(1)	(2)
Farmers	-	-1.659
Managers_Advisors_agri	8.401	8.409***
Gardeners	7.655	4.671
Forestry_and_Hunting	-	35.82***
Mineral_Oil_gas_quarries	-53.81	-802.7
Stone_preparers	-19.91	8.153**
Building_material_makers	-0.106	4.811
Glass_makers	0.660	-
Chemical_workers	0.514	5.279
Plastics_processors	1.183**	5.085
Paper_makers	1.250*	3.429
Printer	-2.301**	-2.578
Wood_preparers	0.490	8.695**
Metal_producers	-2.051	2.718
Moulders	-0.0944	10.89
Metal_moulders_non_cut	1.713**	6.417**
Metal_moulders_metal_cut	-0.563	6.845**
Metal_surface	-0.938	9.343**
Metal_connectors	-	6.742*
Smiths	-0.126	22.52
Sheet_metal	-1.213	4.570
Locksmiths	-0.679	6.237**
Mechanics	-	1.452
Toolmakers	-	5.917
Precision_fitters	0.0494	1.964
Electricians	1.218**	4.070
Assemblers_and_Metal	0.464	7.806**
Spinners	3.049***	81.25***

Textile_makers	1.329	6.014
Textile_processer	1.164	4.415
Textile_finisher	-	8.741
Leather_processing	1.920	6.967**
Bakery_goods_makers	-0.851	-66.70
Food_preparers	-	7.421**
Beverage_or_Luxury_food	-	-35.40
Butchers_Fish_processing	0.0194	-
Nutrition	1.808**	-97.69
Bricklayers_Concrete	-1.383	-43.54*
Carpenters_Roofers	-1.756	-
Building_labourer	-9.803	-14.81
Building_finishers	-	5.584
Room_equip_Upholsterers	-1.480	5.450
Carpenters	0.544	3.819
Painters_lacquerers	-	5.066*
Goods_examiner	0.858	6.393**
Assistants	0.446	7.493***
Machinists	2.980***	5.982*
Engineers	0.716	5.862**
Chemists_Physicists_Math	0.938	3.323
Technicians	0.786	6.277**
Technical_specialists	2.660**	6.270*
Wholesale_and_retail	-0.782	4.660*
Bank_Insurance_spec	8.615*	4.088
Services_agents	-1.967	3.764
Surface_transport	-0.636	2.821
Water_Air_transport	1.147	1.952
Communication	-5.685	6.454**
Warehouse_managers_transport	1.220**	6.318**
Management_consultants	3.296***	6.891**
MPs_officials	-0.103	7.174**
Accountants_Data_processing	1.963**	5.442*

Office_specialists_auxiliary	2.663***	6.797**
Watchpersons	3.318*	5.514
Protective_services	-15.31	7.332
Legal_professionals	31.43***	25.63
Journalists_Librarians	-1.487	18.81**
Artists	-	7.739**
Health_occupations	-15.47	-
Physicians_Pharmacists	-	2.622
Teachers	3.937	-5.775
Humanities_Scientists	1.140	6.108
Attending_on_guests	-	3.677
Body_care_occupations	7.945	-
Housekeeping	-55.16**	-
Cleaning	-2.209	4.896
Job_seeker	-	8.441*
Workforce	2.287***	4.095
Non-penalized in LASSO:		
# of establishments	0.482***	0.222***
Employment growth	0.0689*	0.0367
Share of females	0.535*	-0.193
(Log) wage bill	0.0825	0.552***
Mean wage growth	0.0334	-0.0249
(Log) employees	yes	yes
Region FE	yes	yes
Industry FE	yes	yes
Year FE	yes	yes
Observations	57452	51022
MPSE λ	2.97	2.57

Notes: This table reports the estimated coefficients from a Post-LASSO logit model. The set of included occupational shares is selected by cross-validation finding the model with the lowest MSPE. The MNEs employment size and the industry fixed effects are needed to control for the non-random stratification of non-MNEs. Standard errors are clustered at the treatment level, i.e. firm-level according to Abadie, Athey, et al. 2017.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A first look at the table shows that despite a large overlap, the set of occupation titles selected by the LASSO procedure to predict the propensity to invest abroad is different between the manufacturing and the service sector. Unsurprisingly, the LASSO did not select very specific service occupation titles (e.g. Food prepares or Guest attendant) for the manufacturing sector. On the other hand, few occupation titles are specific to the set selected for the manufacturing sector, and in particular the service sector set includes manual production jobs such as Metal connectors or Machinists.

Focusing on the predictors of the propensity to do FDI in the manufacturing sector (Column (1)), we find that the largest most significant predictors are titles identified earlier as skilled administrative occupations: the highest positive predictor is Legal professionals, followed by Bank and Insurance specialists, Management consultants, Office specialists auxiliary and Accountants and Data processors. These belong to the pool of high-skill occupations which could be complementary to the firm's expansion, and are accompanied by technical manual occupations such as Electricians, Technician specialists and Warehouse managers. We also identify a number of occupations whose skill- and wage-levels are rather low: Spinners, Machinists, Metal molders or Plastic processors. These job titles seem to belong rather to the workforce that could be substituted by production in the offshore affiliates. On the negative side, few occupational titles have a significant negative coefficient in the post-LASSO estimation. Among the elected titles with a negative although not significant coefficient, we find titles related to raw material handling (e.g. Mineral and oil quarries, Stone preparers, Smith and Sheet metal workers) as well as a lot of occupations requiring obvious physical interaction with the end user: Bakers, Carpenters, Wholesale and retail traders or Service agents.

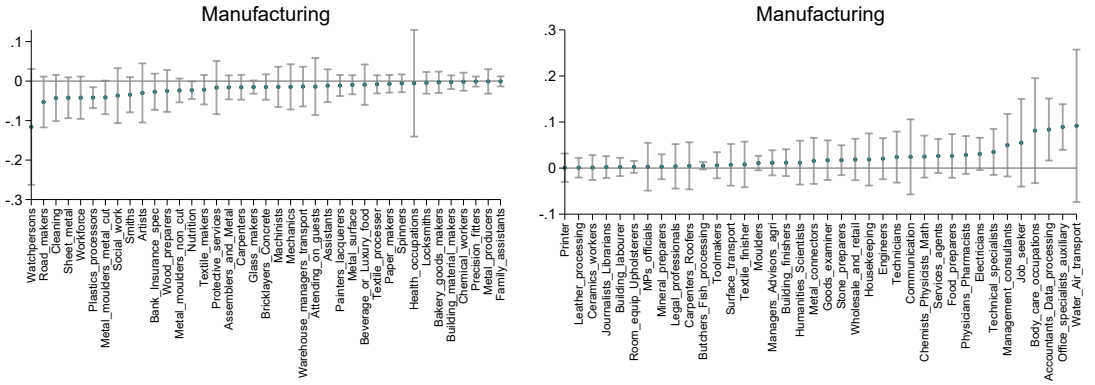
In the service sector (Column (2)), the set of significant positive predictors is larger than the manufacturing one, and we find no significantly negative coefficients. Among the positive predictors of a firm's propensity to open a foreign affiliate, we find numerous administrative and organizational occupations that overlap with the positive predictors in the manufacturing sector (e.g. Office specialists, Accountants, Warehouse managers, Agricultural managers and Management consultants). We also find, in line with our analysis at the coarse occupational and at the task level, a substantial set of titles with a manual/material-output component: Wood preparers, Metal molders, and associated work, Assemblers and Spinners, Machinists, and a set of high-skill production jobs (e.g. Engineers, Technicians and Technical assistant). Services requiring a strong in-presence person and a large degree of interactivity appear as negative predictors of future FDI decisions: Bakers and Food prepares, Teachers exhibit the largest negative coefficients.

This level of analysis thus captures more nuanced effects that are also perhaps more difficult to generalize. Since the multiplicity of fine occupation codes is too heterogeneous, we are comforted in our choice of coarser yet meaningful categories in the main text. We note however, that management and organizational jobs remain systematic strong positive predictors of future FDI decision, a fact that appears very robust throughout our analysis. On the other hand, occupations requiring a strong degree of interactivity or geographic proximity are identified as negative predictors of a firm's propensity to engage in international activities. The role of both skilled and unskilled manual production tasks that are potentially cheaper in the Czech Republic is less clear and robust. We cannot find strong evidence that they are positive predictors of future FDI decisions.

Difference-in-Differences Estimation

We then turn to the results from our matched DiD design (Section 2.4), where the dependent variable is the employment share of a given occupation code o. As before, we consider the employment shift of each occupational title separately.[46] The matching employed in this DiD estimation remains the one from the main text.

Figure C1: Matched DiD Estimates of Fine Occupational Categories - Manufacturing Sector



(a) Negative estimates (b) Positive estimates

Notes: This figure displays estimated occupational composition changes in manufacturing MNEs relative to non-MNEs in response to a FDI. Formally it displays the (separately) estimated coefficient β_{POST} from Equation (2.4) where the outcome is the employment share of the two-digit occupation code o, and associated 95% confidence intervals. Due to the multiplicity of categories, we rank the estimates by size and report negative ones in Panel (a) and positive ones in Panel (b). For a precise description of the methodology, see Section 2.4. Standard errors are clustered at the match-level.

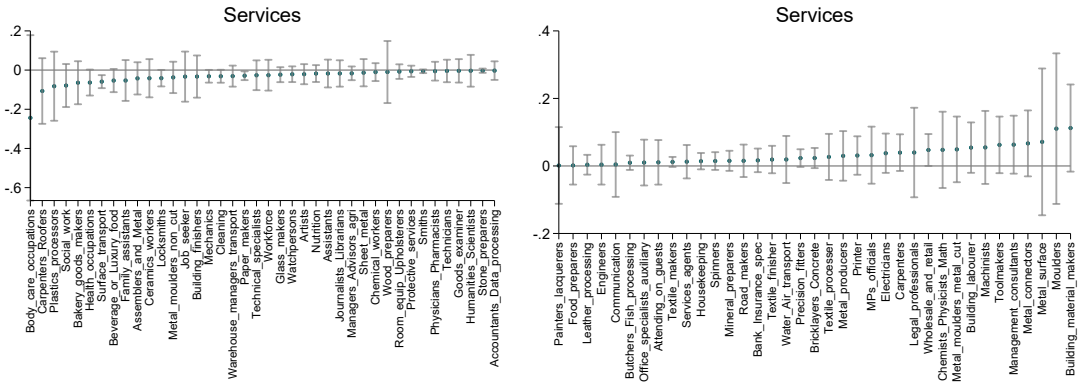
Among the occupation codes with the largest differential in manufacturing firms (Figure C1), we identify mostly manual occupations such as Metal or Plastic workers, Precision construction workers, textile related jobs, and technical specialists. This is in line with our previous results for Blossfeld groups or tasks. Among the jobs that are most complementary with FDI activities, we find medium-skill service jobs: Data scientists and Office specialists auxiliary, Managers[47]; and manual jobs that require in-

[46] For censoring purposes, some occupation codes were dropped, as they represented too few observations. We also excluded agriculture and mining related occupation codes.

[47] The category "Management consultant" also includes senior managing staff and entrepreneurs.

person performance (Electricians, Transportation workers, technicians). This makes intuitive sense: FDI-engaging firms substitute jobs that can be performed in the Czech Republic (seemingly mostly technical or non-technical manual jobs), but need to expand their management and/or analysis activities to facilitate coordination, and reinforcing their local (manual) activities that have to be performed in-person.

Figure C2: Matched DiD Estimates of Fine Occupational Categories - Service Sector



(a) Negative estimates

(b) Positive estimates

Notes: This figure displays estimated occupational composition changes in manufacturing MNEs relative to non-MNEs in response to a FDI. Formally it displays the (separately) estimated coefficient β_{POST} from Equation (2.4) where the outcome is the employment share of the two-digit occupation code o, and associated 95% confidence intervals. Due to the multiplicity of categories, we rank the estimates by size and report negative ones in Panel (a) and positive ones in Panel (b). For a precise description of the methodology, see Section 2.4. Standard errors are clustered at the match-level.

Figure C2 reports the differential employment shifts between FDI-engaging and non-MNE firms focusing on service industries only. The picture looks qualitatively different from Figure C1, with a higher fraction of jobs experiencing positive employment shifts rather than negative ones.[48] Among FDI-*substitutable* jobs, we find health-related occupations (from the private sector: Body-care and other health occupations), janitorial services (Surface transport or Cleaning), catering occupations and a number of manual jobs (Locksmiths, Mechanics, Paper makers amongst the

[48]Because our sample of matched service firms is relatively small, it includes more occupational titles whose effects are censored if they include an insufficient number of observations.

most significant). Among the complementary jobs, we find a more heterogeneous set of job descriptions of professions and management occupations (such as managing directors, warehouse managers, legal professionals), wholesalers and retailers, but also production occupations such as precision fitters or electricians.

Overall, our analysis at the two-digit occupation code level sheds more light on the specific job titles that expand within the broader Blossfeld group, or which jobs drive the changes at the task level.

We further leverage the ranking of occupations from our matched DiD analysis, which allows us to compare the data-driven ranking of actual employment shifts from setting up foreign affiliates with the ranking of occupations in offshorability indices as done in Section 2.5.

D Offshorability

In this section, we describe in detail the replication of the literature-based offshorability indices selected for our analysis in Section 2.5. In particular, we make it explicit how we harmonize these indices for the German classification of occupations (KldB88) at the three-digit level.

Preparation of Indices

We leverage the particular advantage that many of the offshorability measures are constructed for German occupation codes using the BiBB Employment Survey. We can therefore obtain some measures directly from the publications such as the ones by Becker, Ekholm, and Muendler 2013[49] and Brändle and A. Koch 2017. Adapting measures tailored for American occupational codes is however a more involved process.

BK index mapping

The measure by Blinder and Krueger 2013 is created from the Princeton Data Improvement Initiative (PDII) that asks questions directly related to the tradability of jobs in 6-digit American Standard Occupational Classification of the year 2000 (SOC00). Since there is — to the best of our knowledge — no direct possibility to map these values to the German KldB88, we follow Baumgarten, Irlacher, and M. Koch 2018 and use a series of crosswalks and weightings.[50] We start obtaining unique offshorability values for each occupation in the PDII using the (min)mode of the entries. We then map SOC00 to its successor classification SOC10 using 2009 weights from the Occupational Employment Statistics of U.S. labor supply and a crosswalk from the U.S. Bureau of Labor Statistics. In a second step, we map 6-digit-SOC10 to the International Standard Classification of Occupations in 2008 (ISCO08) using

[49] Following the authors' suggestion we preferred the strict definition of offshorability over the lenient one.

[50] We thank Daniel Baumgarten for sharing his crosswalks and ideas on the mapping.

2014 employment weights from U.S. labor supply and the respective crosswalk from the U.S. Bureau of Labor Statistics. In a third step, we map 4-digit-ISCO08 to 5-digit-KldB10 and then to 3-digit-KldB88 using crosswalks and weights of German labor supply in 2014 from the German Federal Labor Agency. Note that, although the mapping creates much distortion, we alleviate much of the concerns by being merely interested in the ranking of occupations and just assigning the top 25% as offshorable.

However, to avoid as much of the imprecision that comes with such recoding as possible, we use a different approach for the replication of measures by Autor, Levy, and Murnane 2003. Similar to Spitz-Oener 2006, we prefer to straightforwardly replicate the the methodology on similar task data in the BiBB Employment survey. Our approach is precisely described in the following.

ALM-SO Measures

Note that the ALM's original data are available online for replication purposes. We could have thus taken the indices as directly applied to the Census occupations from Autor, Levy, and Murnane 2003 and then used several crosswalks and weightings to the German classification of occupation. Several construction choices made by ALM convinced us to not do that: first and foremost, the survey used to describe jobs dates 1970, that is two decades before the time frame our analysis is based on. Given the transitory nature of the 3-digit classification of occupations, a 1970 snapshot is outdated for our analysis that aims to describe jobs in the 1990s. Second, the indices are extrapolated for subsequent years based on the respective distribution of demographics in the survey and mapped to the demographics of the Census data. For German jobs in KldB88-classifications, a weighting by American demographics would create even more noise. Finally, the German Qualification and Employment Survey is in spirit similar to the DOT or the O*Net databases, and updated at a

higher frequency during our sample period. Similar to Spitz-Oener 2006, we decide to replicate the ALM measures using the BiBB Employment Survey and also based on her methodology. However, we still modify the choice of variables used for the aggregation of the indices to stay as close to the ALM original measure as possible.[51]

Baseline rules to select BiBB variables

To select the variables for the replication of the ALM-SO measures, we followed a set of constraining rules that make our replication exercise as conservative as possible:

- Only use variables that repeats themselves in very similar wording across survey waves
- Generate coherent coding: reduce each frequency categories into dummies - as some earliest variables are expressed as dummies.
- Only use variables that directly speaks to the definitions and examples mentioned in the ALM Appendix table.

Exact step by step procedure

Each wave's variables can be roughly decomposed into four types of questions:

1. Activities performed
2. Competencies/Skill required
3. Tools used
4. Working conditions

The stating point is the translation and organization of each wave's variables along these four categories to select the ones that overlaps across studies. We then use the

[51] The detailed list of variables available is provided in the following subsection. In essence we preserve Spitz-Oener 2006 choice of variables and added additional activity and knowledge related variables.

working conditions question in a very specific context: we define a routineness dummy based on the following two questions that are repeated almost word for word in each wave:

> How often would you say in your job are precise directives and steps given to you with strict instructions?
> How often would you say in your job do you have to repeat exactly identical tasks to the detail?

where the first question identifies codifiability and the second question literal routines in the job.

Then for each of the three ALM measures, we select the overlapping variables that either are exactly equivalent of the DOT variables (e.g., "use of Maths", "Eye-hand coordination") or that translate exactly as in the descriptions of the *Handbook for Analyzing jobs* (e.g. "mixes and bakes ingredients", "drives bus to transport passengers"). We deliberately ignored overlapping variables that pertained to activities, skills or tools that could apply to many indices at once.[52]

For each ALM measure we make sure that we use the same Activities, Competences and Tools in each of the three survey waves. We obtain one to three dummies per measure (one dummy for activities in that measure, one for tools and one for skills) that we combine in a $[0, 1]$ measure as follows:

$$RI = \frac{(A_I + S_I + T_I)}{3} \times \mathbb{1}\left[Routine\right]$$
$$NRI = \frac{(A_I + S_I + T_I)}{3} \times (1 - \mathbb{1}\left[Routine\right])$$

Finally, we compound all three wave's measures into one set of five static indices. It is simply the weighted mean of each measure, where the weights are the observations per job in each survey wave.

[52] In that regards, we follow exactly the methodological choices of Spitz-Oener 2006.

In Becker, Ekholm, and Muendler 2013, the aggregation method is slightly different. We follow exactly their description of it: we calculate the average number of non-routine and interactive tasks involved in performing a given two-digit occupation (based on their codification). Second, we find the maximum number of non-routine and interactive tasks required to perform any two-digit occupation. Third, we measure a given two-digit occupation's degree of non-routine and interactive tasks as the ratio between the average number of non-routine and interactive tasks in the occupation and the maximum number in any occupation. We standardize by the maximum and minimum number of tasks in any occupation so that task shares vary between zero and one across occupations. In her methodology, Spitz-Oener 2006 uses dummies, which justifies the different aggregation choices made for the ALM-SO measures relative to the Becker, Ekholm, and Muendler 2013 ones.

Final normalization

One important issue one faces when dealing with job offshorability measures, is the lack of unit to characterize how offshorable an occupation is. Each measure we take from the literature has its own scale to rank jobs. It isn't an issue *per se* when measuring correlations, but we will need a way to identify "offshorable" workers, in a manner that will be coherent across indices. To do so, we use the actual cross-sectional distribution across all years of each index separately. We will define as offshorable a job whose offshorability index belongs to the top 25 percentiles of a measure's distribution. For measures that identify non-offshorable jobs, we will define as offshorable a job whose index belongs to the bottom 25 percentiles of that measure's distribution. They are thus taking the value 1 if a worker is defined "offshorable", and zero otherwise.

Final variable use

Table D1: Final variables used in Becker et al. 2013

Nonroutine tasks			Interactive tasks		
Strict	Lenient		Strict	Lenient	
v32, v64, v65,	v32, v34, v40,		v69, v70, v71,	v54, v61, v62,	
v66, v67, v70,	v49, v50, v51,		v73, v74, v75,	v69, v70, v71,	
v71, v93, v94,	v52, v54, v55,		v76, v77, v78,	v73, v74, v75,	
v95, v97, v104,	v56, v57, v58,		v79, v80, v81,	v76, v77, v78,	
v106, v108,	v59, v60 v61,		v82, v83, v93,	v79, v80, v81,	
v109, v110,	v62, v64, v65,		v94, v95, v97,	v82, v83, v84,	
v111, v113,	v66, v67, v69,		v98, v99, v110,	v85, v86, v88,	
v114, v115, v116	v70, v71, v77,		v116	v89, v90, v92,	
	v78, v79, v80,			v93, v94, v95,	
	v92, v93, v94,			v96, v97, v98,	
	v95, v97, v100,			v99, v108, v109,	
	v102, v103,			v110, v116	
	v104, v106,				
	v108, v109,				
	v110, v111,				
	v113, v114,				
	v115, v116				

Notes: This table is replicated from BEM's list of BiBB Employment Survey variable use. All variables are from the 1998/99 survey wave.

Table D2: Final variables used in Braendle and Koch 2017

Index	1992	1998	2006
COD	v184	v265	f411_02
ROU	v185	v266	f411_03
SUM	v38, v39, v40, v41, v42, v43, v44, v45, v46, v47, v48, v49, v50, v51, v52, v53, v54, v55, v56, v57, v58, v59, v60, v61, v62, v63, v64, v65	v189, v190, v191, v192, v193, v194, v195, v196, v197, v198, v199, v200, v201	f303, f304, f305, f306, f307, f308, f309, f310, f311, f312, f313, f314, f315, f316, f317, f318, f319a
COM	Subset of variables from SUM	Subset of variables from SUM	Subset of variables from SUM
ICT	v140, v141, v160, v161, v162, v163, v164, v166	v53, v54, v55, v56, v57, v59, v60	f320, f324, f1001_02
INT	v189, v190	198	f325_03, f325_06, f325_07
LOC	Use occupation classification	Use occupation classification	Use occupation classification
LAW	v95, v96	v223, v224	f403_04
WRI	Imputed	v124	f403_09
LAN	v274, v275, v276, v277, v278, v279	v726, v727, v728, v729, v730, v731, v732, v733, v734	f406_01, f406_02, f406_03, f406_04, f406_05, f406_06, f406_07, f406_08, f406_09, f406_10
NEW	v186, v187	v267, v268	f411_04, f411_05, f325_01, f325_05

Notes: This table lists the replication variables for the strict offshorability measure by Brändle and A. Koch 2017. The variables are from the BiBB Employment Survey waves 1991/92, 1998/99, and 2006/07.

Table D3: Final variables used in the replicated ALM 2003 measures

Wave	NRA	NRI	RM
1992	v186, v187, v77	v190, v64	v38, v39, v50, v130, v134, v135, v136, v137, v138, v139
1998	v267, 268, v213	v195, v198	v112, v113, v31, v33, v34, v35, v36, v37, v38, v39, v40, v44
2006	f411_04, f411_05, f325_01, f325_02, f311, f403_08	f325_03, f325_04, f325_07, f310	f303, f305, f308, f403_02, Tools: 100, 101, 103, 104, 105, 106, 107, 200, 201, 202, 203, 204, 205, 206
Routineness dummy is created with variables v184 and v185 in the 1992 wave, v265 and v266 in the 1998 wave, and f411_02 and f411_03 in the 2006 wave.			

Notes: This table reports a list of the BiBB Employment Survey variables used in our replication of the ALM-SO measures. An initial set of variables from the 1998/99 survey wave is borrowed from Spitz-Oener 2006. All additions of extra variables is our own. All variables are from the 1991/92, 1998/99 and 2006/07 survey waves.

Chapter 3

Exploring the "Fissured Workplace": Fragmentation of Internal Job Ladders and Workers' Careers[1]

3.1 Introduction

Decades of technological progress and falling costs of transportation and communication have drastically changed the way in which firms organize their production. The development of practices such as automation and outsourcing have pushed firms to

[1]This work is supported by a public grant overseen by the French National Research Agency (ANR) and is part of the "Investissements d'Avenir" program (reference: ANR-10-EQPX-17 - Centre d'accès sécurisé aux données (CASD)).
I am extremely grateful to my advisors Stephen Redding, Alexandre Mas and Eduardo Morales for their guidance in this project and their invaluable suggestions and encouragement. I am indebted to Adrien Matray, Richard Rogerson and Esteban Rossi-Hansberg for their sustained comments on my work. I also thank Treb Allen, Adrien Bilal, Andrew Bernard, Damien Capelle, Teresa Fort, Gene Grossman, Anders Humlum, Federico Huneeus, Oleg Itskhoki, Elisa Jacome, Steve Mello, Fernando Parro, Nina Pavcnik, Charly Porcher, Robert Staiger, as well as numerous seminar participants at Dartmouth College and Princeton University for helpful discussions and comments. This research benefited from financial support from the International Economics Section (IES) and the Industrial Relations Section (IRS) at Princeton University. Their support is gratefully acknowledged.

specialize in their "core competencies" i.e. the activities that generate the largest value added and are the hardest for competitors to imitate, while delegating other activities to contractors. This new paradigm raises concerns about the consequences of the "fissured workplace"[2]:

> *Over the past few decades, major companies throughout the economy have faced intense pressure to [focus] their businesses on core competencies [...] by shedding less essential activities.*
>
> *Opportunities for "climbing the ladder" fade because the person in the mail room (or, more likely, at the IT service desk) is now a subcontractor without a pathway. This not only means lower wage growth [...], but also diminished opportunities for [...] other pathways to upward advancement.*
>
> *Taken together, the fissured workplace makes the workplace for many workers a more challenging and risky place to earn a living.*
>
> - Weil 2014 -

In this paper I document that the fissured workplace has become a growing and widespread phenomenon since the 1990s, and I explore the associated costs and benefits for plants and workers from reorganizations towards fissured structures.

Consider a view of a firm as a hierarchical pyramid of activities with different roles in the production process and different responsibility levels. These levels, or *layers*, constitute an internal job ladder for workers. When firms specialize in their highest value-added generating activities, they do so by displacing (fissuring) parts of the internal job ladder outside of the plant. What are the returns to such reorganization? For workers, opportunities for climbing the ladder may fade because they are employed in specialized workplaces with *fissured* internal job ladders. The progression

[2]Weil 2014 - *The Fissured Workplace: How Work Became So Bad for So Many and What Can be Done to Improve It?* - Harvard University Press

of workers' earnings may well stagnate in response to the new organization. Conversely, if the firm specializes, workers may benefit from an increased total surplus, provided this surplus is shared and if workers become more productive.

Using French matched employer-employee data, I first construct a new occupational job ladder that accounts for workers' paths across different hierarchical layers of skill requirements and management responsibilities, and their associated earnings progression over time. Pairing this ladder to data on the universe of French private employers, I then document how firms and plants have re-organized their internal job ladders away from pyramidal structures and towards hollowed-out ones. In a third part, I use a matched difference-in-differences empirical design to describe how reorganizing plants, and thus workers' environment, evolve after the fragmentation, while controlling for selection on observables. Further matching workers within matched plants, I then estimates how this affects workers' careers. I consider the impact of the fragmentation of internal job ladders on both displaced and retained workers employed in layers adjacent to the fragmented layer.

This paper makes four contributions. First, by constructing an occupational job ladder based on workers' occupational transitions over their professional life cycle, I can emphasize the decline in promotion rates for young workers employed in entry-level jobs between 1995 and 2015 in France. I also show how the distribution of organizational structures in the French economy moved away from pyramidal internal job ladder structures between 1995 and 2015. Firms have changed the way they organize production at the plant level by increasingly adopting a job ladder that has lost its middle layer or shrunk so much that only a single layer remains. This is what I identify in my data as the "fissured workplace". My second contribution is to document that adoption of the fissured workplace at the plant level is associated with growth-inducing events. My next two contributions nuance the fissured workplace narrative concerning workers' outcomes. In a third contribution I provide

empirical evidence to confirm the fissured workplace narrative regarding the decline in opportunities for upward mobility. In comparison with control workers employed at the same level in non-fragmenting plants, workers employed at the bottom of the fissuring ladder of fragmenting plants are on average 65% less likely to be promoted (to climb up the occupational ladder, either within-plant or between-firm), despite being employed in expanding plants. Fourth, I nuance the negative perception of these reorganizations of labor markets, by showing that these same retained workers employed at the bottom of the hierarchy in plants where the middle layer has disappeared see their gross earnings increase by 2.2% in response to a fragmentation event, while displaced workers experience long-lasting wage losses of 16% on average. There is ambiguity regarding the costs and benefits of the fissured workplace for workers.

I construct a new occupational job ladder based on an iterative clustering algorithm applied on a pre-period panel of workers whom I follow across occupations, plants and firms over ten years. I find that workers' careers defined as movements up and down this ladder primarily take place at the plant level: 74% of all occupational transitions occur within-plant, and 78% of all transitions occur up the ladder. This will motivate an analysis focused on plant- or worker-level results abstracting from firm level outcomes.[3] Young workers entering the labor market at the bottom of the occupational job ladder in 2015 experience slower upward mobility than cohorts entering the labor market in 1995, as their promotion rate in the first 15 years of their career is 80% lower. Using data on the universe of French private employers over two decades, I then document the ways in which firms and plants have re-organized their internal job ladders. I first compare the distributions of organization types across firms in 1995 and in 2015. In 1995, 69% of all French private employers had an organizational structure with two or more adjacent layers of the occupational job

[3]In principle, the methodology developed in this paper can be easily extended to consider firm level outcomes. In a future research, I intend to focus specifically on the differences in the way firms and plants within these firms reorganize.

ladder. By 2015, this proportion had fallen to 58%, while the share of plants with only one layer of the job ladder or a hollowed-out ladder had increased accordingly. This trend is stronger at the plant level than at the firm level, but is present in both distributions. Taking this fact as given, I then study the evolution of plants' average number of layers and workforce concentration across these layers over my whole sample. I control in turn for size, regional and industrial composition effects, as well as for age of the firms. I find that the transition towards the fissured workplace is most prevalent in the growing service sector and amongst new entering plants that are more concentrated.

I use a matched difference-in-differences design to explore the changes in plants' performance and workers' careers associated with a plant's reorganization from a pyramidal to a fissured structure. In order to address selection of plants into different organizational forms on observables, I match fragmenting plants with similar plants whose job ladder remains unchanged. I then pair this matching with a difference-in-differences design and check for common pre-trends to verify that plants are on a similar path prior to the fragmentation, and assess selection on unobservables. To pin down the fragmentation of internal job ladders, I use plant-level data to identify the disappearance of an entire occupation code from the middle layer of the plant's ladder. When comparing the outcomes of fragmenting plants with their matched controls before and after the re-organization event, I find that in the aftermath of a transition towards a fissured organization, plants' sales increase by 13.6% after ten years. This reflects an increase in a plant's value added of 13.3% and in multi-factor productivity by 3.8%. I find that fragmenting plants also see their employment grow by 10.8% over the same time frame. This employment growth appears to be driven by the long-lasting increase in the share of workers with specialized technical skills (both high- and low-skilled). Taken together, these results provide evidence that the fissured workplace is associated with positive performance gains of the plants that

appear to specialize in their highest valued-added generating activities. My empirical design is not exempt of a possible omitted variable bias such as an idiosyncratic demand shock that could induce both the fissuring of the workplace and an increase in a plant's sales and value added.[4] For this reason, I do not interpret these findings as causal responses to the fragmentation of the job ladder, but as evidence of the changing working environment faced by employees in fissured workplaces.

To analyze the impact of the fissured workplace on workers' careers and earnings profiles, I compare workers employed in fragmenting plants to a control group of workers sharing the same characteristics employed in matched non-fragmenting plants. The matching of workers within matched plants allows me to control for selection on observables and the sorting of workers into workplaces with different dynamics. I consider the impact of the fragmentation of internal job ladders on both displaced workers whose occupation is fragmented, and retained workers employed in layers adjacent to the fragmented layer at the time of the reorganization.

I confirm the fissured workplace narrative regarding the decline in opportunities for upward mobility among retained workers at the bottom of the job ladder. Compared with control workers employed at the same level in non-fragmenting plants, and despite being employed in expanding plants, these workers are on average 65% less likely to be promoted. Despite the loss of internal opportunities, they are not significantly more likely to change employer in order to seek better opportunities on the external labor market. I do not find similar declines in upward mobility for displaced workers, who are twice more likely than similar workers retained in non-fragmenting plants to change employer in the three years following their initial displacement, but whose promotion rates remain unchanged. Workers employed in the hierarchical layer above the fragmented one are little affected: I estimate that their upward mobility is

[4]See for example L. Caliendo, Monte, and Rossi-Hansberg 2015.

not changed, although they are on average 42% more likely than similar workers in non-fragmented plants to change employer in the future.

My results on wages, however, deviate from the fissured workplace narrative. Retained workers employed at the bottom of the hierarchy in plants where the middle layer has disappeared see their gross earnings increase by 2.5% in response to a fragmentation event, and this gain remains present even after five years. Conversely, I find that workers at the top of the hierarchy in specializing plants do not experience any wage increase, again despite being employed in expanding plants. I argue that this wage response to the fissured workplace is consistent with two mechanisms. First, earnings responses for retained workers are suggestive of compensating differentials in wages, in particular for workers at the bottom of the ladder. However, the negative and significant wage response of displaced workers (-35.6% on impact, -15.9% on average), and the absence of any wage gain for retained workers at the top of the fragmented ladder suggest as a second mechanism changes in workers' rent-sharing environment. Displaced workers' careers are not "interrupted" in the sense that they remain relatively mobile, but their earnings are durably decreased. On the other hand, the differential wage responses of retained workers' earnings below and above the fragmented layer in the context of an expanding employer suggest that the fissured workplace may generate a reshuffling of workers' rents depending on their position in the job ladder.

Literature

This paper relates to several literatures. Documenting the empirical relevance of internal job ladders and the organization of firms poses a challenge. This is due to the lack of detailed information on workers' occupations over time, both within and between firms. To tackle this issue, one of the most common strategies in the literature has been to rely on survey data from a single firm (Baker, Gibbs, and Holmstrom 1994a).

Alternatively, papers have focused on managerial occupations (Baker, Gibbs, and Holmstrom 1994b, Gayle, Golan, and Miller 2015, Friedrich 2018, Pastorino 2019), thereby ignoring the careers of those at the bottom of the distribution. A second limitation is the lack of a clean separation between the identifiers of firms and those of plants. Focusing on single establishment firms is problematic as it misses out a large fraction of employment and potential restructurings of internal labor markets between plants within firms (Cestone et al. 2017). I contribute to this literature by focusing explicitly on plants, and by using matched employer-employee data previously used to estimate the fixed effects of both workers and firms (Abowd, Kramarz, and Margolis 1999) to construct and generalize a definition of an occupational job ladder that can be used to describe workers' careers both within plants, and between plants of the same firm or across firms.

I also contribute to the literature that develops the theory of the organization of firms as a knowledge hierarchy (Garicano 2000, Garicano and Rossi-Hansberg 2006). This literature defines a firm's internal organization as a set of hierarchical layers, gathering employees with similar characteristics and knowledge and performing similar tasks within the organization. In their paper, L. Caliendo, Monte, and Rossi-Hansberg 2015 use the same data to carefully document the existence of such hierarchies in French manufacturing firms between 2002 and 2007. They do not, however, consider the dynamic evolution of these organizations over time and across sectors. At the macroeconomic level, Harrigan, Reshef, and Toubal 2016 have described the growing job polarization of the French labor market, and estimated how this trend decomposes between a within-firm and a between-firms component. H. Egger, Kreickemeier, et al. 2016 have proposed a theoretical model of offshoring contributing to this trend. I provide micro-level evidence of a new potentially important contributing factor of this trend: the emergence of the "fissured workplace" as an organizational

paradigm that contributes to both an occupational polarization within-plant, and a specialization of activities between plants.

My matched difference-in-differences strategy builds on the theoretical literature on firms' outsourcing and offshoring decisions. The concept of a firm's "make-or-buy" decision can be traced back to Coase 1937. I use insights both from the literature that considers industry-specific heterogeneity (Grossman and Helpman 2002, Grossman and Rossi-Hansberg 2008 and Grossman and Rossi-Hansberg 2012), and from models of heterogeneous firms (Antràs and Helpman 2004, L. Caliendo and Rossi-Hansberg 2012, Chaney and Ossa 2013). I use the theoretical determinants of fragmentation proposed in these papers to build my matching algorithm and construct a control group of non-fragmenting plants sharing similar incentives to reorganize based on observable variables. Amongst potential explanations for a firm's reorganization, Bergeaud et al. 2021 show that the diffusion of broadband internet in France led firms to outsource non-core occupations and to become increasingly homogeneous in their occupational composition. They find that in response to such events, firm productivity and demand for high-skill workers is increased. Bernard, Fort, et al. 2020 document that offshoring firms continue domestic production of the same goods they offshore, but in higher-quality varieties. In the broader context of within-plant re-organization, I find that fragmenting plants shift their employment towards specialized occupations and that they experience increases in productivity and value added.

The main focus of the empirical literature on the micro-level impact of outsourcing and automation has been on the displaced workers. Papers focusing on outsourcing of specific service occupations have established a wide range of earnings effects in the form of wage loss (Dube and E. Kaplan 2010 focus on janitors and guards; Goldschmidt and Schmieder 2017 focus on on-site outsourcing of janitorial and catering workers; Hummels et al. 2014 estimate the impact of offshoring on different skill-

types). Drenik et al. 2020 use novel temp agency data to consider all types of temp service workers, and find a penalty for being outsourced of 51% of the workplace-specific pay premia earned by regular workers. Few of these papers consider the mobility effects associated with outsourcing or offshoring. My paper is closest in methodology to Goldschmidt and Schmieder 2017, who establish that outsourcing reduced mobility between employers. I contribute to this literature in several dimensions. First, I broaden the scope of occupations considered: my empirical strategy does not rely on the identification of specific industry or occupation codes; rather, I let the data tell me which of these occupations are susceptible to being fragmented by plants. Second, I estimate the effects of a fragmentation of the internal job ladder on both displaced *and* retained workers, thereby broadening the focus of the micro-level analysis on all workers. Finally, I provide empirical evidence of the effects of such reorganization on detailed career-level outcomes rather than limiting myself to wage responses alone, and in particular on upward mobility across firms and occupations in the medium- to long-run.

Finally, I contribute to the rent-sharing literature, in particular in response to trade (Frías, D. S. Kaplan, and Verhoogen 2012, Card, Heining, and Kline 2013, Macis and Schivardi 2016, Helpman, Oleg, et al. 2017): while I do not use the methodology proposed by Abowd, Kramarz, and Margolis 1999 and used in these papers, and adopt a strategy closer to that of Kline et al. 2019, I emphasize a new margin of firm heterogeneity susceptible to participating in a change in the rent-sharing environment of workers.

In Section 3.2, I present my data and describe the construction of a new measure of the occupational job ladder in France. In Section 3.3, I use this measure to document changes in the organization of plants over time in France. Section 3.4 describes my matched difference-in-differences empirical strategy, and discusses the identification.

I estimate the causal impact of the "fissured workplace" on plants in Section 3.5 and on workers' careers in Section 3.6. Section 3.7 concludes.

3.2 Data and the construction of the Internal job ladder

3.2.1 Data sources

In order to obtain a clear definition of internal job ladders and careers, I need detailed information on the workforce composition of firms (skills and occupations), as well as workers' history of employment both within and between firms over long periods of time. I use French administrative data and combine several sources of information.

The DADS (*Déclarations Annuelles des Données Sociales*) is a large-scale administrative database of matched employer-employee data. The data are based on mandatory employer reports of the earnings of each French employee subject to French payroll taxes. It covers the universe of private employers over the period 1995 to 2015, with an average of 2.2 million plants per year (1.3 million firms per year), and provides detailed information on a plant's workforce for each calendar year, the number of employees hired in each of the two-digit codes of the French classification of occupations, associated average wages, as well as detailed industry and geographical location of the plant. It also provides unique plant and firm identifiers, which allows me to follow plants over time, as well as firms and the structure of plants within-firm over the same time period. One version of the DADS at the job level provides information on individual workers in these same plants in each calendar year, but only allows workers to be followed over two consecutive years. While this enables the measurement of workers' inflows and outflows between plants and firms, it does not make it possible to consider the long-term career path of any individual worker.

I therefore complement this dataset with the *Panel Tous Salariés*. This panel randomly selects all workers born in October of an even year since 1976, and extracts information about them from the job-level DADS each calendar year. This allows me to follow a 1/24 sample of the population over time and throughout their professional life cycle. Starting in 2002, the sample is doubled to allow the selection of workers born in October of an odd year as well.[5] The panel provides detailed information on workers' demographics, location of work, gross and net wages, hours worked, and occupation code. It also provides the employing plant and firm identifiers, which allows me to link each worker of the panel to her employer's organization structure at each point in time. For a subsample of the individuals in the panel, I can also complement this information with data on their education level at their first appearance in the sample (by matching with the *Échantillon Démographique Permanent*).[6] Combining these two datasets provides me with maximum information on workers' careers and employers' characteristics.

I complement plant- and firm-level data with FICUS, which contains information on firms' balance sheets and income statements from the universe of company tax files. The data can be easily matched to the DADS using the firm's identifier. This allows me to consider sales and value-added, as well as measuring the productivity of firms over time.

I remove agricultural occupations from my sample (codes 11 and 69), as well as public servants and workers employed for more than 2 years in any of the relevant public-sector occupations (codes 33, 45 and 52) because labor market dynamics for French public servants meet very different criteria.[7] Finally, I exclude self-employed workers (included in the panel starting in 2009). In the resulting sample I have 2.9

[5] I use the full sample because it allows me to consider a larger population, and I control for calendar year to adjust for sample size and age distribution changes.

[6] This subsample represents about 300,000 unique individuals, in a sample that includes about 3.6 million unique individuals.

[7] I also removed clergy (code 44) as it became obvious after careful analysis of the data that these occupations were "absorbing states" and did not allow for any type of career paths for workers.

million unique individual identifiers between 1995 and 2015, with an average of 1.3 million individuals observable each year.

3.2.2 The organization of firms in light of workers' careers

Intuitively, a career is the natural occupational path a worker will follow through job titles, from her entry into the labor market to her retirement, within and between employers.[8] I generalize this definition at the level of the aggregate economy in a pre-period sample. The occupational job ladder is defined as a series of layers that corresponds to a worker's progression within the occupational hierarchy of firms. This definition ought to be broad enough that it can identify a common hierarchy across firms in different sectors (and thus includes very different occupations), while allowing me to identify promotions and demotions not only within firms, but also between employers.

My strategy follows insights developed by Baker, Gibbs, and Holmstrom 1994a in their construction of a job ladder for the single firm they study. I focus on a panel of workers between 1984 and 1994, whom I can follow between occupations and firms over that ten-year window.

I start by identifying entry-level jobs for each gender and education-level group by considering the most frequent first full-time occupation codes for individuals aged between 15 and 35.[9] Table A2 in Appendix A describes this first stage: while there is

[8] Doeringer and Piore 1971 defined a career solely at the level of the firm, by entry-level jobs and a set of occupational transitions through the firm's hierarchy. It is with this definition in mind that Baker, Gibbs, and Holmstrom 1994a analyze their unique firm data: they measure internal worker flows across occupation codes, and identify the most frequent path across job titles.

[9] One key challenge for my analysis is the possibility of using a detailed yet consistent classification of occupations over time. The French administration provides a four-digit classification starting in 1993, but it is poorly documented by employers before 2009. I therefore use the two-digit classification of occupations, which has the advantage of being completely consistent between 1982 and 2009. In 2009, the change in the four-digit occupation classification led to a more precise codification of jobs otherwise classified as intermediate without further clarification: this generates a change in the two-digit classification as well. I nonetheless extend my analysis to 2015, based on the observation that aside from the year 2009 (which unfortunately also coincides with the period in which France entered a major recession) none of the aggregate series in employment and firms'

substantial variation between genders, only three occupation codes appear to be exclusively available to workers with a university degree (and correspond to intermediate level supervision activities). I therefore pool all these jobs with the exception of the university-degree-specific codes into what I call the bottom layer of my hierarchy.[10]

In a second step, I construct a yearly within-plant occupation-to-occupation transition matrix, which I then aggregate over the period 1984 to 1994. The use of within-plant occupational transitions only, excluding between-firm transitions, is motivated by two reasons. First, this paper studies changes that occur in internal job ladders. The definition of the organization of firms that I am developing must apply to workers' internal moves between occupation codes and tasks when this environment is changing. Second, as I will show in the next section, the vast majority of French workers' transitions between occupation codes occur within a plant, and not between firms or even across plants within a firm.[11] I construct a transition matrix for each gender $\times$ education-level $\times$ ten-year age bin cell. I pair it with an occupation-to-occupation wage transition matrix, obtained by regressing individual wages in a destination occupation on a set of within-plant origin-occupation dummies, a year fixed effect and the initial worker's wage.[12] I then proceed recursively: starting from those occupation codes I identified as entry-level, I define as the next hierarchical step the most frequent transition from an entry-level job to a non-entry-level job that

composition exhibit particular structural breaks from 2010 on. Appendix **??** describes the French 2-digit classification of occupations, and details how I adjust occupation code series over 2009 for individual workers' transition. The year 2009 is excluded from all of my empirical analyses for these reasons.

[10]By construction, it is equivalent to allowing high-skill workers to enter the labor market directly in higher hierarchical layers.

[11]This is also in line with the focus on within-firm occupational transitions in Doeringer and Piore 1971's definition of internal labor markets, and is directly comparable to Baker, Gibbs, and Holmstrom 1994a; Baker, Gibbs, and Holmstrom 1994b's monograph.

[12]For these regressions, I abstract from the age dimension and pool all years, but maintain a distinction between education-level groups and gender in order to have enough observations to identify the wage gain or loss.

involves a wage gain of at least 10% of the starting wage.[13] For most of my entry-level jobs, this represents a stable group of occupation codes that constitutes my second hierarchical layer. I continue this procedure until I have assigned each occupation code to a layer. The result is a decomposition of occupation codes into four hierarchical layers described in Table 3.1. This classification of occupations codes into layers is robust to using a Wald-clustering algorithm, after characterizing each occupation (initial cluster) by a vector of within-plant transition probabilities and share of external entry into an occupation, and ranking subsequently clusters by average wage.[14]

Table 3.1: Definition of hierarchical layers

Layer	CS2 codes	Examples	Average (gross) wage
4. SMEs business owners & CEOs	21, 22, 23	Top managers of small craft or industrial businesses, CEO	65,270
3. Supervision & management jobs	34, 37, 38	Managers and senior staff, chief engineer, lawyers	54,941
2. Intermediary jobs	43, 46, 47, 48	Sales executives, industrial architects, forepersons	28,040
1. Entry-level jobs	68, 67, 65, 64, 63, 62, 56, 55, 54, 53, 42, 35	Receptionists, cashiers, janitors	16,577

Note: This table describe the composition of each hierarchical layer resulting from my construction process in terms of two-digit occupation codes. Yearly gross wages are in constant 2010 euros.

[13]The choice of 10% as a metric is directly inspired from Baker, Gibbs, and Holmstrom 1994b who find that promotions are on average associated with a 6 to 8% wage gain within their firm. The average wage gain associated with within-layer occupational transition is below 2%.

[14]Note that the hierarchical layers thus defined are coarse enough that moving from one group to the next most likely entails more than a mere change of job title, and also includes some changes in tasks and responsibilities. This hierarchy also coincides almost exactly with the definition of firms' hierarchy employed by L. Caliendo, Monte, and Rossi-Hansberg 2015 in their description of the organizational structure of French firms based on the one-digit French classification of occupations.

With this classification, I can define an individual worker's career as her progression through these hierarchical layers both within and between firms, and the associated earnings changes. I also characterize an employer's organizational structure using the set of hierarchical layers present in a firm's workforce at any point in time. This is what I will refer to as the internal job ladder of a firm or a plant (subsequently IJL).

3.2.3 The importance of within-plant internal job ladders

Panel A of Table 3.2 reports summary statistics on workers' professional mobility and reveals the importance of the plant as the unit of observation for workers' careers. 74% of all changes between occupation codes happen *within a plant*, whereas only 7% happen between plants within the same firm, and 18% between firms.[15] The average yearly probability of changing occupation is 11%, whereas the average probability of changing employers (firms) is 4%. A *promotion* is defined as an occupational transition (within *or* between employers) that involves moving to a higher hierarchical layer than the current one.[16] I find that 30% of all occupational changes occur as a promotion, versus 22% as a demotion (a transition down the ladder). Demotions are not particularly rare (average yearly probability of 1.9%, compared with an average probability of promotion of 2.6%), a feature of the French labor market already highlighted by Kramarz, Postel-Vinay, and Robin 2014.[17] Consistent with the choice of a plant's IJL as unit of observation, I find that 78% of all promotions happen within a plant.

[15] Conditional on belonging to a multi-establishment firms, 71% of workers' occupational switches occur within-plant, 12% within-firm across plants, and 17% to a different employing firm.

[16] Table A4 in Appendix A verifies that any promotion thus defined does imply a wage gain, even when the promotion is paired with a change of employer. I find that a promotion between employers represents a larger wage gain of almost 35% depending on the fixed effects included.

[17] Interestingly, the wage losses associated with movements down the ladder are lower than the wage gains occurring when a worker moves up. This can be related to wage rigidities and a relatively strong (although on the decline) unionization of the French labor market. In this respect, one should think of these demotions as a change in status and in a worker's future career dynamics.

Panel B focuses on promotion opportunities for workers according to their place in the ladder. It takes longer for workers at the bottom of the ladder to reach the intermediate level, than for Layer 2 workers to be promoted. In the majority of the cases, Layer 3 is the end point of a worker's career. The relevance of internal job ladders is illustrated by the fact that the share of promotions that occur in-house increases as workers climb the ladder.

To further emphasize the relevance of considering the career of workers at the bottom of the job ladder, I estimate the average change in yearly promotion rates of young workers aged 15 to 30 years old relative to a cohort of workers entering the labor market in 1995. More specifically, I define a worker's cohort as the year she enters the labor market in her first full-time job. Relative to the group of workers entering the labor market in 1995, I plot the average promotion rate of younger cohorts, while de-trending the aggregate business cycle and controlling for gender and age at entry. I compare cohorts over time, and control successively for the three-digit industry code in which workers begin their employment, the location of their first employment spell, and the specific occupation code they work in for the first time. I plot the trends in Figure 3.1.

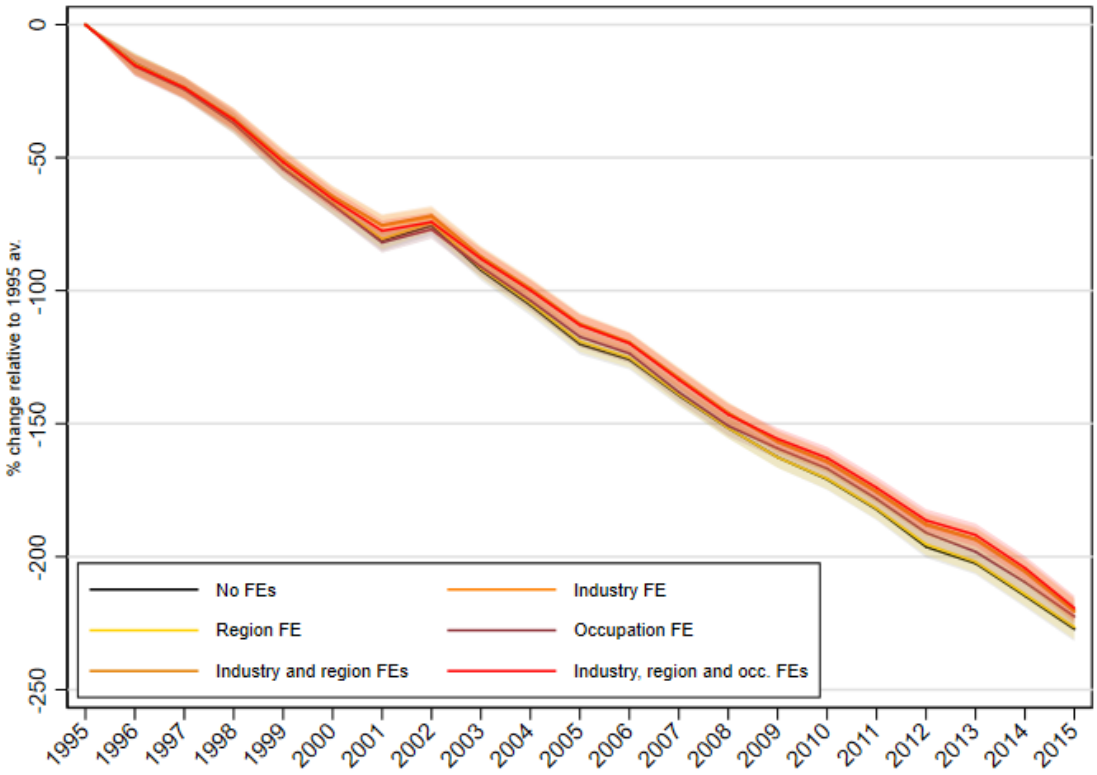
Conditional on age at entry and gender, young workers entering the labor market in 2015 are on average more than twice less likely to be promoted in the first years of their career than workers entering the labor market in 1995. The average promotion probability of young workers in entry-level jobs at the beginning of their career has monotonically decreased during my sample. This appears to be true even within local labor markets defined by the industry and location of the first employment spell of a worker. There is a very clear occupation composition effect at play in this picture. When comparing workers of the same gender entering the same occupation code at the same age, the decline in the promotion rate between the cohort of 2015 and that of 1995 is less pronounced, but nevertheless represents an 80% decrease in the

Table 3.2: Summary statistics - Workers' sample

	Mean	Std. dev.	Median	N (millions)
Panel A: Full sample				
Age	37.57	11.88	37	29.8
Gender	0.57	0.50	1	29.8
Gross yearly income	23,018.22	282,330.2	19,886.45	26.6
Tenure at firm	4.44	4.96	2.55	26.6
Tenure at plant	3.74	4.30	2	26.6
Prob. of switching plant	0.079	0.27	0	22.9
Prob. of switching firm	0.041	0.20	0	22.9
Prob. of within-firm plant switch	0.037	0.19	0	22.9
Prob. of switching occupation	0.11	0.32	0	22.9
Share of occupational switches in-house	0.74	0.44	1	2.58
Prob. of switching layer	0.049	0.22	0	26.9
Prob. of promotion	0.026	0.16	0	22.9
Share of internal promotions	0.78	0.41	1	0.77
Prob. of in-house promotion	0.021	0.14	0	22.9
Prob. of external promotion	0.004	0.06	0	22.9
Prob. of demotion	0.019	0.14	0	22.9
Share of occupational switches as promotion	0.30	0.46	0	2.58
Share of occupational switches as demotion	0.22	0.41	0	2.58
Panel B: Layer specific samples				
Layer 1				
Prob. of promotion	0.027	0.16	0	13.1
Share of in-house promotions	0.79	0.40	1	0.35
Share of within-firm between plants promotion	0.08	0.27	0	0.35
Share of external promotion	0.13	0.33	0	0.35
Layer 2				
Prob. of promotion	0.045	0.20	0	3.9
Share of in-house promotions	0.81	0.39	1	0.17
Share of within-firm between plants promotion	0.10	0.29	0	0.17
Share of external promotion	0.09	0.29	0	0.17
Layer 3				
Prob. of promotion	0.008	0.09	0	2.6
Share of in-house promotions	0.85	0.36	1	0.02
Share of within-firm between plants promotion	0.06	0.24	0	0.02
Share of external promotion	0.09	0.29	0	0.02

Note: Summary statistics on the full sample of workers between 1995 and 2015. Earnings variables are in constant 2010 euros, and tenure variables are expressed in years.

Figure 3.1: Average promotion rate for young workers in entry-level jobs



Note: This figure reports the average promotion rate of young workers aged 15 to 30 years old by cohort. A cohort is defined as the year these workers enter the labor market for the first time in a full-time job. Each line represents the time series of estimated cohort fixed effects in an equation of the form: $y_{it} = \delta_\tau + \beta X_{it} + \gamma_{j(i,\tau)} + \gamma_{r(i,\tau)} + \delta_t + \varepsilon_{it}$ where y_{it} is worker i's probability of being promoted at time t. The coefficient of interest is δ_τ, which identifies the cohort-specific average promotion rate, with τ being the year of entry of worker i on the labor market. $\gamma_{j(i,\tau)}$ is a fixed effect for worker i's three-digit employing industry at τ, while $\gamma_{r(i,\tau)}$ is a county fixed effect that controls for the location of her first employment spell. The black line reports the raw average time series. The yellow line reports the cohort fixed effects after controlling for location of the first employment spell. The orange line controls solely for industry fixed effects, while the dark orange line controls for the local labor market (industry $\times$ location). The maroon line reports the coefficients in a specification with occupation code at entry fixed effects. The red line reports the coefficients from the full specification.

average promotion rate. The monotonic decline in young workers promotion rates is robust to considering promotions within plants. In fact, the decline in average internal promotion rate between cohorts entering in 1995 and in 2015 is larger and represents a 90% decrease.[18]

[18]Time trends in average rates of internal and external promotion rates are displayed in Appendix **??**.

While there are many possible reasons for such a decline in promotion rates over time, the emergence of fissured internal job ladders appears as one possible important contributing factor to these trends.

Table 3.3: Summary statistics - Plants' sample

	Mean	Std. dev.	Median	N (millions)
Employment	63.43	1,359.35	23	6.12
Gross payroll (thousands of €)	2,585.24	16,000	679,355	5.28
Share of plants in multi-est. firms	0.45	0.50	0	6.12
Number of occupations in-house	4.89	3.43	5	6.12
Number of hierarchical layers	2.28	1.27	3	6.12
Concentration across layers	0.56	0.31	0.59	6.12
Share of entry-level jobs	0.67	0.29	0.77	5.13
Share of intermediary jobs	0.21	0.22	0.13	5.13
Share of supervision jobs	0.11	0.18	0.04	5.13
Share of management jobs	0.01	0.04	0	5.13

Note: Summary statistics on the full sample of plants between 1995 and 2015, excluding observations with fewer than 11 employees. Payroll is expressed in constant 2010 euros.

Table 3.3 reports summary statistics on employer plants in my sample and reveals the hierarchical nature of plants' organization. When excluding very small businesses of fewer than 10 employees, I find that the median plant employs 23 workers in 5 distinct occupations spread into 3 distinct hierarchical layers. Consistent with what L. Caliendo, Monte, and Rossi-Hansberg 2015 find with their classification, the average establishment has a pyramidal structure and employs 72% of its workforce in entry-level jobs, 17% in intermediary positions, 9% in supervisory occupations and 2% in management jobs.[19] I discuss in more detail changes in these structures and the shape of IJLs over time in the next section.

[19]One important issue with the fourth layer of the identified ladder is that at the plant- or firm-level, it is not necessarily reported. In particular, business owners do not appear in the worker panel and are not reported as employees in the DADS *postes* (whereas CEOs are). As a result, I always assume that firms and plants do have a Layer 4 in-house, and focus on the organization of the remaining three layers.

3.3 The "fissured workplace" as organizational paradigm

How do firms organize their workers, and has this changed over time? Since A. Smith 1776's pin factory, many typologies of the organization of firms have been proposed.[20] I document here the emergence of a new organizational paradigm in France between 1995 and 2015.

I examine the distribution of plants' organizational structures over time.[21] Based on my definition of the IJLs of firms, I can identify six main types of organizational structures, reported in Table 3.4: plants organized with only one layer; plants organized with two out of three hierarchical layers; plants with all three layers; and plants with the complete hierarchy of Layer 1 to 4.[22,23] I consider both the raw distribution of plants across organizational structures when discussing levels, and the distribution weighted by a plant's employment when discussing changes, in order to understand how this translates into a change of organization for individual workers. Both types of distribution behave similarly, and with similar magnitudes in changes. I therefore focus my analysis on the employment-weighted distribution.

Two things are to be noted from this table: the relative importance of pyramidal structures in levels across all years in the distribution of plants, and the strong reallocation of structures in changes between 1995 and 2015 away from the traditional pyramid. Firms with only one layer represent 33% of all the firms in my sample, 90% of which have only Layer 1. Plants with the full pyramid from Layer 1 to 3 or

[20] See Morgan 1986 for the first typology of management practices.

[21] The analysis of the structure of firms is left for Appendix B.

[22] This latter structure has to be identified separately from a structure with Layers 1 to 3, despite the assumption that there is a manager in every structure. This is due to the fact that while business owners are not reported in the DADS, other top-level employees (like CEOs, COOs, etc.) will be reported in Layer 4 if they represent more than one person.

[23] Note that this list does not exhaust all the possible combinations of hierarchical layers within a plant. I verify that the remaining possibilities are negligible in my sample: they represent 0.01% of the plants and the firms in my sample.

1 to 4 represent 18% and 25% of my sample respectively. Between 1995 and 2015, the share of plants organized with only one hierarchical layer more than doubled. Almost all of these changes are driven by the increase in the share of plants with only Layer 1 (+5.76 p.p.). Of those plants organized with two hierarchical layers, the most important change in the distribution pertains to plants organized with only Layer 1 and Layer 3 in-house: their share of total employment multiplied by 5 (from 1.61% of employment in 1995 to 5.38% in 2015). In contrast, the employment share of plants organized sequentially (Layer 1 and Layer 2 or Layer 2 and Layer 3) did not change much. Plants with a pyramidal hierarchy with Layer 1 to 3 or 1 to 4 represent 82.17% in 1995, and 72.11% in 2015. The share of three-layer structures remain important and stable, but the employment share of four-layer organizations shrinks significantly (from 34% to 23.6%). The qualitative pattern that arise on aggregate is robust to considering separately the service or the manufacturing sector. In particular, the growth of the one-layer organization is generalized, but the disappearance of plants with layers 1 to 3 is more pronounced in the service sector.[24]

In order to identify the dynamic time trend in the organizational changes discussed above, I estimate the yearly change in the average number of in-house layers and workforce concentration across these layers relative to 1995 in Figure 3.2. I control in turn for plant size, three-digit industry code and location (county).[25] Appendix B presents firm-level results.[26]

[24] At the firm-level (Table B2), the resilience of the pyramidal structure of hierarchies is much stronger, despite the disappearance of four-layer firms (whose share in the distribution declined by 32%). The employment weighted share of three-layer firms (Layers 1 to 3) increased by 10p.p. between 1995 and 2015, and the share of structures with Layers 1 and 2 increased by another 2p.p. This stands in contrast with the plant-level distribution, and reflects a weaker emergence of fissured firm-level organizations.

[25] In the French data, this corresponds to a *département*: a geographical division of France. There are 95 of them in the metropolitan territory, and an additional 6 overseas. The median area of a *département* is a little under 6000 km^2, with a wide disparity in terms of population density.

[26] There is an overlap between plants and firms, as 69% of the plants in my sample are single-establishment firms.

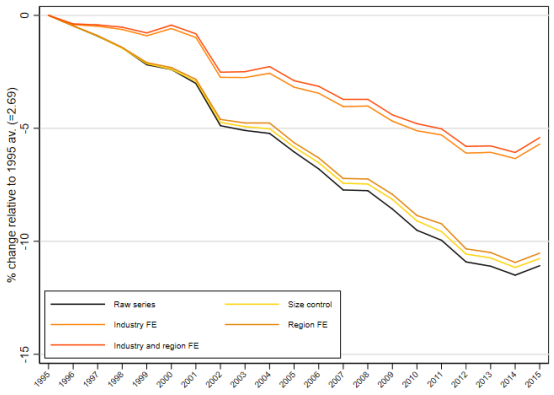
Table 3.4: Distribution of organizational structures - Plant level

Structure	1995	2005	2015	All	1995	2005	2015	All
Only one layer	28.22	34.67	34.84	32.92	5.20	8.44	10.96	8.76
Layer 1 + Layer 2	15.04	21.02	13.17	16.13	10.79	13.85	10.82	12.10
Layer 1 + Layer 3	3.68	4.55	7.93	5.40	1.61	2.59	5.38	3.32
Layer 2 + Layer 3	1.04	2.10	1.42	1.57	0.31	0.92	0.75	0.73
Layers 1, 2 and 3	18.67	20.61	17.68	18.06	48.14	50.23	48.54	48.93
All four layers	34.10	17.16	25.32	26.25	34.03	23.98	23.57	26.19
Pyramidal structure	95.27	93.35	90.64	93.02	98.08	96.48	93.87	95.95
Two layers structure	19.76	27.67	22.52	23.10	12.71	17.36	16.95	16.15
Weighted	No	No	No	No	Yes	Yes	Yes	Yes
N	559,011	900,522	964,273	18,706,677	526,970	838,301	821,838	16,404,856

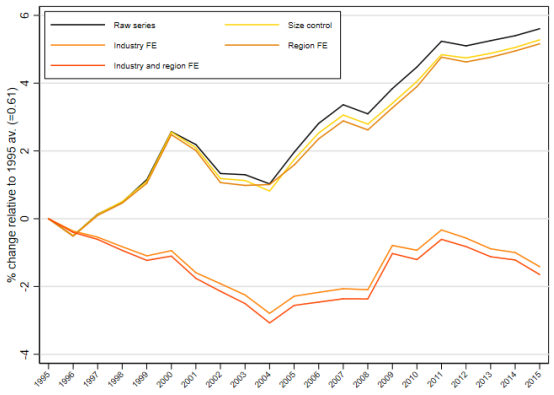
Note: This table reports the frequencies of several organizational structures in my sample of establishments, overall and over time. Unweighted frequencies report the share of all plants in the sample with a given organizational structure. Weighted frequencies are weighted by plant's employment.

Figure 3.2: Plant-level organization of layers

(a) Number of layers



(b) Workforce HHI



Note: This figure reports the average number of hierarchical layers present in a plant's workforce (Fig. 3.2a) and the average Herfindahl-Hirschman index of workforce concentration across these layers (Fig. 3.2b) over time. Each line represents the time series of estimated year fixed effects in an equation of the form: $y_{ut} = \delta_t + \beta Y_{ut} + \gamma_{j(u)} + \gamma_{r(u)} + \varepsilon_{ut}$ where y_{ut} is a plant u-level outcome at time t describing a plant's current organization. The coefficient of interest is δ_t, which identifies the year-specific average across units of observation. $\gamma_{j(u)}$ is a fixed effect for plant u's three-digit industry, while $\gamma_{r(u)}$ is a county fixed effect that controls for plant u's location. The black line reports the raw average time series. The yellow line reports the time fixed effects after controlling for establishment number of employees. The sand line adds to this specification a *département* fixed effect. The light orange line reports the coefficients in a specification with size control and three-digit industry fixed effects. The dark orange line reports the coefficients from the full specification.

I find a very clear decrease in the length of the internal job ladder over time, both at the plant level and the firm level, and a strong associated increase in the concentration of workers into a few of the remaining layers. Figure 3.2a report the average number of layers within a plant over time. Focusing on the raw series first, it shows a monotonic decrease between 1995 and 2015 and is 11% lower in 2015. This trend is significant even after controlling for plant size. While geographical composition seems to contribute to the overall trend, the most important composition effect comes from controlling for industry fixed effects: including all controls, the average number of within-plant layers within narrowly defined local labor markets is 6% lower in 2015 than in 1995. Figure 3.2b reports the Herfindahl-Hirschman index of a plant's workforce force concentration across the IJL's layers[27]; conditional on an IJL's length, this index reports the concentration of workers into a few or many of these layers. The higher the index, the more concentrated the workforce into only a few layers. While the raw time series exhibits an increase in average workforce concentration across layers of almost 6%, controlling for industry inverts the trend starting in 2004. Within narrowly defined industries, the average concentration of workers across hierarchical layers in-house declines steadily between 1995 and 2003, and then increases to about 1% lower than the 1995 average (0.61) in 2015. The importance of the industry fixed effects suggests that this trend is driven by growing industries.

In order to explore the industry-composition effect emphasized, I report the same time series separately on manufacturing, service and commerce and transportation sectors (Figure 3.3). While the decline in the number of layers is generalized across sectors, there is a clear divergence in terms of workforce concentration between man-

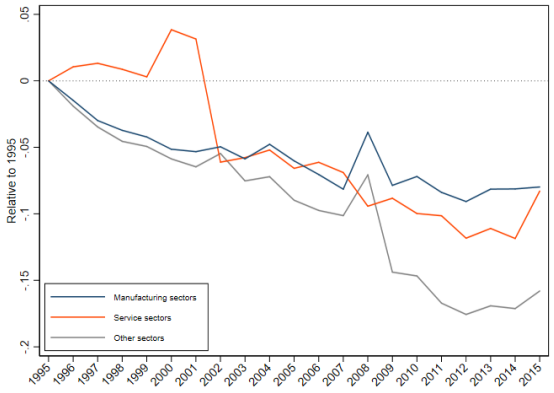
[27]Formally:

$$y_{ut} = \frac{1}{N_{ut}^2} \sum_l N_{lut}^2$$

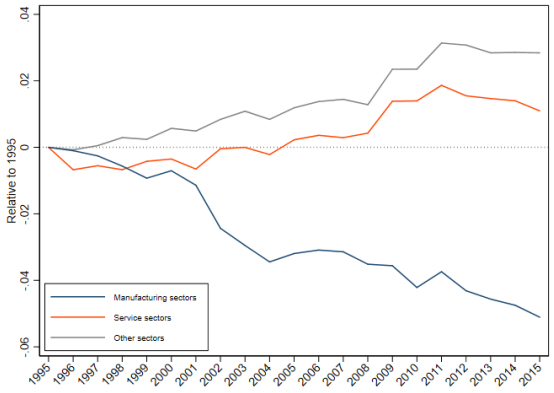
, where N_{lut} is the number of employees in layer l available in plant u at time t and N_{ut} is plant or firm total employment.

Figure 3.3: Plant-level organization of layers by sector

(a) Number of layers



(b) Workforce HHI



Note: This figure reports the average number of hierarchical layers present in a plant's workforce (Fig. 3.3a) and the average Herfindahl-Hirschman index of workforce concentration across these layers (Fig. 3.3b) over time. Each line represents the time series of estimated year fixed effects in the following specification: $y_{ut} = \delta_t + \beta Y_{ut} + \gamma_{j(u)} + \gamma_{r(u)} + \varepsilon_{ut}$ where y_{ut} is a plant u-level outcome at time t describing a plant's current organization. The coefficient of interest is δ_t, which identifies the year-specific average across units of observation. $\gamma_{j(u)}$ is a fixed effect for plant u's three-digit industry, while $\gamma_{r(u)}$ is a county fixed effect that controls for plant u's location. The navy line is estimated on the manufacturing plants of my sample. The orange line is estimated on the plants belonging to the service industries. The grey line pools plants from the construction sector, the transportation sector, and the wholesale and retail trade sector.

ufacturing plants and the rest. The trend in IJL's narrowing is particularly strong in the services, commerce and transportation sectors. However, and consistent with Bernard, Fort, et al. 2020, I find that in France too, firms in the manufacturing sectors tend to "diversify" in the sense that they adopt more horizontal structures.[28,29]

To summarize, I show in this section that firms have substantially changed the way they organize their workforce and therefore the shape of their internal job ladders over the past two decades. These effects are particularly strong at the plant level. Pyramidal structures have been replaced over time by what I identify as the fissured

[28] At the firm-level (Figures B1a and B1b in Appendix B), I find similar trends but in much lower magnitudes, suggesting that firms' re-organization is mostly focused on the restructuring of individual plants.

[29] In Appendix B, I also explore the age-dimension in these trends. Similarly to the industry-level analysis, while the decrease in the average number of layers is generalized, the workforce concentration trends are increasing for new entrants but decreasing for incumbent plants and firms, suggesting a potentially strong between-firm component in these changes.

workplace: one-layer organizations and hollowed-out structures of the type Layer 1 and Layer 3 with no middle layer. This translates into shorter IJLs and an increase of workforce concentration around narrower sets of activities.[30] While this confirms the narrative of the emergence of the fissured workplace as a new organizational paradigm, the question remains whether this change has any significance for plants' performance and workers' careers.

3.4 Research design

I use a matched difference-in-differences framework to estimate how plants' performance and workers' career evolve in the aftermath of a plant's IJL fragmentation. The challenge here is that plants' organization is endogenous: there is non-random selection of plants into different organizational form, and the decision of changing the current structure is also endogenous.[31] The matching part of my design allows me to compare treated and control units with ex-ante similar organizational structures. The rationale for the matching procedure is driven by the need to control for selection of plants into organizational structures and reorganization status on observable variables. The double-differences event study provides visual evidence of the evolution of key plant- and worker-level outcomes around the year of the fragmentation. It also allows me to check for pre-trends and address the concern that treatment and control units could be on different trajectories prior to the reorganization. I thereby verify that I observe a parallel evolution of treated and control units in years leading to the

[30] All these results are also true at the occupation code level.

[31] One potential path to establishing a causal relation between plant's IJLs and plant and worker outcomes is to instrument changes of organizational structures. Finding an instrument that would satisfy the exclusion restriction of only affecting firm and worker outcomes through a plant's reorganization may prove challenging. Moreover, such a design does not allow me to consider the dynamic response of plants and workers to a change from one organization to the next, in particular from a pyramidal structure to a fissured structure. The difference-in-differences design allows me to consider not only changes between two dates, but the whole dynamic response of plants and workers to the fissured workplace.

reorganization. It finally allows me to control for time-invariant heterogeneity across firms.

I first formally define the event and associated treatments considered, and then discuss the matching procedure and the endogeneity concerns it aims at addressing. Finally, I present the estimating equations.

3.4.1 Definitions

Internal job ladder fragmentation

I use a plant's workforce outflows to identify groups of workers employed in a specific occupation leaving a plant at the same time. I say that a plant u fragments occupation o at time τ if:

1. Plant u loses its last worker in occupation o at time τ
2. Plant u had at least 10% of its workforce employed in occupation o in the two years prior to τ
3. Plant u does not hire any new worker in occupation o over the next three years
4. Plant u's employment *excluding* occupation o does not decrease by more than 10% between $\tau - 1$ and τ

Condition (1) paired with condition (3) are key in defining a fragmentation event: an occupation is said to be fragmented if it was part of the production process at time $\tau - 1$, and disappears durably from it after τ.[32] Condition (2) ensures that I am considering occupations that are integral parts of the production process (at least 10% of the workforce), which means that more than one worker is displaced at once

[32] In essence, I use condition (3) (on post-event variables) to correct for potential attenuation bias. It may be that many plants "fragment" an occupation at time τ only to have it re-appear in the IJL one year later to adjust for temporary shocks. If that were happening, my estimates would be biased towards zero. I estimate the intent-to-treat correction that would be required to be 59%. Condition (3) is an alternative to this type of correction. All my results are robust to ignoring condition (3).

in the majority of the events. The two-year time window prior to the fragmentation event in condition (2) is meant to reflect the fact that this kind of fragmentation takes some time to happen. In fact, while the fragmentation is completed at time τ, the data reveals that these events usually start at $\tau - 2$.[33] Finally, condition (4) ensures that I consider a healthy plant, and that I do not capture a response to a negative shock pushing a declining plant to lay off workers.[34] Note that this latter condition induces selection on plants' prior growth trajectories. It is therefore crucial in the matching procedure to consider control plants fulfilling a similar condition.

Note that nothing in this definition of my events guarantees that I am considering arm's length outsourcing events. A plant could fragment an occupation because the parent firm is moving that activity to a different plant (internal outsourcing). I could also capture implementation of new technological processes allowing a plant to automate an occupation, and thus substituting occupation o for capital.[35] My focus is solely on identifying organizational changes that reflect a (permanent) change in the hierarchy of the plant, based on the observation that workers' relevant internal labor markets are essentially within plants. I exclude from my sample plants with 10 employees or fewer because reorganizations towards fissured structures are only relevant for firms with more than one layer.

Table 3.5 describes the type of fragmentation events identified with this definition. This definition of fragmentation events identifies occurrences where a majority of plants eliminate entry- or intermediate-level jobs. Those are either business service

[33] I find that a two-year window is the most reasonable: at $\tau - 3$ I find no significant decline in plants' workforce for those plants that I know will subsequently abandon an occupation; at $\tau - 1$ these plants are already on a declining trend, which suggests that the workforce shedding started earlier.

[34] I do not constrain my event to happen sequentially, so that one plant could be fragmenting several occupations at once. The restriction on workforce decline partially prevents this, on purpose.

[35] In their paper, Goldschmidt and Schmieder 2017 have a more specific definition of fragmentation events that is directly associated with on-site outsourcing: they identify movements of workers in catering or janitorial occupations from one employer to the next in manufacturing industries, imposing that these workers remain in the same occupation and work in the same location.

Table 3.5: Fragmentation events characteristics

Top 5 occupations fragmented		Top 5 fragmenting industries	
Occupation	Frequency (%)	Industry	Probability (%)
67. Unqualified production workers	10.36	14. Metallurgy and metal processing	4.26
68. Unqualified craft workers	8.76	9. Manufacturing of mechanical equipment	3.88
46. Intermediate administrative & commercial occ.	8.08	12. Chemistry, rubber and plastic industry	3.88
63. Qualified craft workers	8.03	7. Automobile industry	3.28
54. Clerical workers	5.93	25. R&D	3.24
# events = 297,594			

Note: The left panel of this table reports the frequencies of the five most frequently dropped occupations in % of overall fragmentation events, excluding 2009. In the right panel I report the share of fragmenting plants for the five industries with the highest shares, in % of all plants in that industry, excluding 2009.

occupations or low-skill production activities.[36] Despite the manufacturing sector being more likely to fragment an occupation, it only represents 16% of all my identified events. The majority of the events I observe occur in the commerce and transportation sector (30% of my events), or in service industries (15% of my events). These frequencies, in line with the aggregate trends presented in Section 3.3, reveal that a majority of the events I identify as fragmentation occur in increasingly specializing non-manufacturing sectors.

Workers' treatment

While the definition above allows me to identify treated plants and consider the differential plants' performance in the aftermath of a fragmentation, the fissured workplace narrative has more to say about workers' outcomes. I therefore need to define a treatment at the individual-level. I focus my analysis on the effect of reorganizations on retained workers experiencing a change in their IJL.[37]

In practice, I consider two treatments for these retained workers. First, I consider workers who see their employing plant fragment an occupation that belongs to the

[36] Among these codes, the group of unqualified production workers (code 67) has seen a large decline in its employment share in the economy between 1995 and 2015. To some extent, these jobs ought to be treated differently than other jobs whose employment share in aggregate remained stable over time, because their disappearance may point to offshoring or automation trends more clearly than pure reorganizations. In my main analysis I will focus on fragmented jobs whose employment share did not change between 1995 and 2015.

[37] The term "retained" can be misinterpreted: I do not impose that these workers remain with the fragmenting plant after the fragmentation event, but solely *at* the time of the event.

hierarchical layer immediately *above* the one they belong to. I label them as retained workers "from below". The exact definition of their treatment is as follow:

1. Worker i is employed in plant u between $\tau - 2$ and τ
2. Worker i see employing plant u fragment (according to the definition above) occupation o of layer L at time τ
3. Worker i is employed in layer $L - 1$ in plant u between $\tau - 2$ and τ[38]

Second, I consider workers who see their employing plant fragment an occupation in the layer *below* the one they belong to (labeled as retained workers "from above"). The definition of the treatment is symmetric to the treatment of the retained workers from below: instead of being employed in layer $L - 1$ at time τ they are employed in layer $L + 1$.[39]

For completeness I also consider as a third treatment the fragmentation of a worker's occupation by her employing plant. I define as "displaced worker" an individual such that:

1. Worker i sees plant u fragment (according to the definition above) occupation o at time τ
2. Worker i was employed in occupation o in plant u at time $\tau - 1$
3. Worker i changes employer (i.e. not only the plant identifier but also the firm identifier) between $\tau - 1$ and τ

The characteristics of the treated workers largely depend on the layer in which they they are employed. When considering retained workers, the main group of

[38] I find that on average about 5% of workers employed in layer $L - 1$ at time τ are individuals previously employed in layer L and demoted to layer $L - 1$ in order to be retained despite the fragmentation of their layer. In order to focus on workers truly attached to the bottom layer of the ladder, I exclude these individuals from my sample by restricting attention to workers employed in layer $L - 1$ throughout the reorganization.

[39] Again, I exclude workers employed in layer L at $\tau - 2$ or $\tau - 1$ and promoted to layer $L + 1$ during the reorganization. They represent 15% of treated observations in that sample.

interest will be workers employed in Layer 1 experiencing the fragmentation of an occupation from Layer 2. Intuitively, they are the ones who should experience an "interruption" in their career due to the reduced opportunities for promotion inside the plant. I also consider retained workers "from above" employed in Layer 3 when Layer 2 is fragmented.[40] For displaced workers, I focus on workers displaced due to a fragmentation of Layer 1. As documented above, they belong to the layer the most often fragmented by plants, and make up the group most commonly referred to in discussions of the effect of outsourcing and automation on workers.

The median treated worker is older, has been on the labor market for longer, earns a higher median yearly wage and is more likely to be male the further up the hierarchy one goes. The median displaced worker is younger and more often employed in a part-time contract than the retained workers.

3.4.2 Matching procedure and discussion about identification

There are three main endogeneity concerns in the context of my analysis. First, the selection of plants into specific organizational structures prior to any reorganization. Second, just as outsourcing and automation decisions are not exogenous, plants' reorganization of their IJL is an endogenous decision. Finally, workers are selected into plants and firms, so that individual outcomes will be correlated to the type of organization they work in. My matching strategy and the choice of variables used are driven by these considerations.

I match treated plants first with similar control plants, and then workers within these two groups of plants. I use a coarse exact matching procedure. This matching strategy is similar to a number of recent papers implementing a dynamic difference-in-

[40] Alternatively, I can consider retained workers above employed in Layer 2 in the case of a fragmentation of Layer 1 as a robustness test. Outcomes for this subsample of workers are presented in Appendix E.

differences research design (Hombert and Matray 2020, Arnold 2020, Jaravel, Petkova, and Bell 2018, Goldschmidt and Schmieder 2017, Jäger 2016).

I start with a sample of 250,310 plant $\times$ year events. I identify treated plants that fragmented at least one occupation during my sample period, and focus on the fragmentation of occupation codes belonging to the two bottom layers of my hierarchy: the entry-level jobs, which represent the bulk of the fragmented jobs, and the intermediate-level jobs, also often fragmented and part of the change in organizational structures documented in Section 3.3.[41] Similarly, I identify as potential control units plants that *never* fragmented an occupation during the same time period. I require all plants to have at least 11 employees and positive employment between years $[t-2, t+1]$. These two conditions are inherent to the definition of the fragmentation events, and therefore need to be applied to potential control units.

I match plants along four dimensions. First, in order to address the selection of plants into specific organizational structures on observables, I match on size — which is tied to the number of layers adopted by a firm (L. Caliendo, Monte, and Rossi-Hansberg 2015) — and a plant's age approximated by a plant's employment growth rate, which I showed in Section 3.3 to be of importance in driving aggregate trends of organizational choices. More specifically, I impose that treated and control plants belong to (i) the same decile of employment size at $t-2$ and (ii) the same quartile of annualized growth rate in number of employees between $t-4$ and $t-2$. Second, I match firms on 1-digit industry code and location at the county level to account as much as possible for geographic or sectoral shocks.[42,43] Third, in order to

[41] Note that because of the pre- and post-period requirements in my definition of a fragmentation event, I identify such events only between 1997 and 2013.

[42] Empirical evidence abounds that outsourcing and automation are more prevalent in some industries than others (Helper 1991, Autor, Dorn, and Hanson 2013b, Autor, Levy, and Murnane 2003, Acemoglu and Restrepo 2019, see Grossman and Helpman 2002, Grossman and Rossi-Hansberg 2008, Acemoglu and Autor 2011 and Grossman and Rossi-Hansberg 2012 for linked theories) and are linked to geographical variations (Chinitz 1961, Autor, Dorn, and Hanson 2013b).

[43] I use a pairing of the French NES36 and A38 classifications (which replaced the NES36 in 2008), which yields a total of 32 coarse industries. Exact matching on the three-digit industry code is too demanding for the data.

capture possible heterogeneity in *task*-specific productivities which would drive the type of fragmentation implemented (Akerman and Py 2014), I impose that treated and control units belong to (iii) the same quartile of annualized growth in the ratio of workers in Layer 2 over workers in Layer 1 between $t-4$ and $t-2$.[44] Finally, in the specific context of outsourcing, the cost-saving motive emphasized by Grossman and Rossi-Hansberg 2008, and other wage considerations such as wage fairness and income distributions (Akerlof and Yellen 1990, H. Egger and Kreickemeier 2012), imply that the plant's position in the distribution of the total wage bill will be an important observable to control for. I therefore impose that treated and control units belong to (iv) the same quartile of $t-2$ total payroll distribution in the economy.

This gives me a total of 31,219 matches (16,658 matches associated with the fragmentation of an occupation in Layer 2, and 14,561 associated with a fragmentation in Layer 1).[45] The matching is quite restrictive and leads to the loss of many treated plants due to the lack of common support for some variables. I find a control plant in 53% of cases.

Table C1 (respectively C2) in Appendix C compares moments of targeted as well as untargeted variables in the sample of treated plants and their matched controls, when the event is a fragmentation of an occupation in Layer 2 (respectively Layer 1). In both panels, the average plant has 30 employees spread across three hierarchical

[44] One strategy would be to match plants on multi-factor productivity as a proxy for selection on unobservable idiosyncratic firm productivity, as suggested in models of heterogeneous firms (Antràs and Helpman 2004, L. Caliendo and Rossi-Hansberg 2012, Chaney and Ossa 2013). This idiosyncratic productivity is likely to be correlated with pre-event trends and post-event outcomes, and can generate a strong omitted variable bias. The direction of this bias is ambiguous, however. In theories of the organization of the firm, such as Garicano, Lelarge, and Van Reenen 2016 or L. Caliendo and Rossi-Hansberg 2012 an expansion of production processes by the most productive firms could lead to a "layering" of the firm with a stronger vertical structure at the firm level. In Antràs, Garicano, and Rossi-Hansberg 2006, for example, depending on the overlap of skill distributions across economies and the level of communication costs, either the least or the most productive firms will engage in outsourcing via the creation of international teams. Instead, I exclude value added and multi-factor productivity from my matching, and subsequently verify parallel pre-trends of treated and control plants for these variables.

[45] I drop events occurring in 2009 from the sample of events prior to the matching, because of the changes in the classification of occupations discussed previously.

layers. Between 50% and 70% of them are employed in Layer 1. Treated plants have slightly lower sales and gross value added than their matched controls. About 40% of all fragmentation events involve the fragmentation of the occupation code 46, which groups intermediary administrative and commercial jobs (such as accountants, legal clerks or advertisement assistants), around 25% of my events are associated with the fragmentation of technicians, and about 10% of events involve the fragmentation of intermediate social services occupations (that are not related to the public sector).[46,47]

Under this matching, the identifying assumption of my empirical framework is that — conditional on all the matching variables — fragmentation decisions of treated plants are driven by exogenous idiosyncratic shocks to plants (such as shocks to productivity, to the cost of fragmenting, or specific organizational structure costs, or to managerial abilities).[48] While this does not allow me to make causal inferences, as I may estimate the effect of both plants' reorganization and unobservable idiosyncratic shocks, it allows me to isolate the effect of these idiosyncratic shocks when they are associated to reorganizations of plants' IJL.

At the worker level, the literature on sorting (Lopes de Melo 2018, Card, Heining, and Kline 2013, Eeckhout and Kircher 2011, Atakan 2006, Shimer and L. Smith 2000, Grossman and Maggi 2000, Abowd, Kramarz, and Margolis 1999, Kremer and Maskin 1996) emphasizes that the matching of workers with firms is not exogenous. This being the case, any estimation on workers' outcomes suffers from a risk of omitted

[46]Note that the total sum of frequencies exceeds 100%: this is because in some rare cases more than one occupation in the same layer is dropped at the same time (and occasionally the whole layer is removed altogether, though this is rarer still)

[47]Plants fragmenting an occupation from Layer 1 (Table C2 in Appendix C) are larger but also exhibit a three-layer organizational structure, with 60% of their workforce employed in entry-level jobs. The majority of the fragmentations of Layer 1 I find involve the elimination of unqualified and unqualified production workers, as well as (unskilled) clerical workers.

[48]Specific examples of such shocks in the French context are the progressive roll-out of high-speed internet in France across cities, allowing firms to suddenly decrease their communication costs as in Malgouyres, Mayer, and Mazet-Sonilhac 2019, or the improved connection of cities to the public transportation network as in Charnoz, Lelarge, and Trevien 2018. In the former case, the data used are not yet publicly available. In the latter example, the timing of the instrument is outside the scope of my dataset.

variable bias that would bias my effects downwards in particular for retained workers (determinants of fragmenting decisions negatively affecting workers' outcomes would be accounted for in my δ_t coefficients).

To address this issue, I do not restrict my plant-level matching to one-to-one and initially keep as many control plants as possible associated with a given treated plant to maximize the pool of potential control workers for each treated unit. Within the treated plants, I extract each treated worker employed two years prior to the fragmentation event.[49] For each treated worker I find at least one control worker in one of the associated control plants. Workers are further matched exactly on (i) the layer they are employed in between $t-2$ and t, (ii) their 2-digit occupation code at the time of the event, (iii) their part-time status at $t-2$ and (iii) their age (four 15-year bins).[50]

Due to the restrictive nature of the matching of workers within matched plants, I do not match on other pre-period variables. I verify afterwards that I obtain a good sample balancing on untargeted variables. This leaves me with a total of 5,702 treated workers, and 9,653 controls, each treated worker having on average two associated control workers. I keep all control workers that meet the matching criteria.[51,52] Under this matching, the identifying assumption is that the career trajectories of treated

[49] This tenure restriction is meant for identifying workers with some form of attachment to the plant, and is similar (though shorter) to tenure restrictions used in the mass layoff literature (Manchester, Watcher, and Song 2009, Davis and Watcher 2011, Lachowska, Mas, and Woodbury 2019).

[50] Note that I do not match on gender: occupation codes are strongly gendered in the French data, and are absorbed in the matching on occupation codes. As is clear from Table A2, for the majority of Layer 1 and Layer 2 jobs, the two-digit occupation codes are overwhelmingly occupied by men only or by women only. Adding gender as part of the matching reduces the sample size even further, without improving the pre-trends or changing the estimates.

[51] Alternatively, I could have chosen a unique counterfactual worker or plant based on a propensity score. This is usually done to avoid the need to weight the data appropriately to obtain balanced samples of treated and control units. Due to the sample size limitation, I keep all controls. I discuss the sample's balancing below.

[52] In order to verify threats to the stable unit treatment value assumption, I verify that I do not have many treated workers gathered in just a few treated plants. I find that about 30% of my treated individuals share their employer with one or several other treated workers.

workers would be similar to those of control workers in identical positions within identical plants in the absence of the fragmentation event.

Table 3.6: Balancing of treated and control workers - Fragmentation of Layer 2

	Treated workers	Control workers
	(1)	(2)
Panel A: Workers from below - Layer 1		
# unique ID	3,860	6,830
Worker's characteristics - Targeted moments		
68. Unqualified handicraft blue collars	1.22	0.69
67. Unqualified industrial blue collars	5.03	3.94
65. Storage and transport occ.	3.89	2.99
64. Drivers	5.60	5.70
63. Qualified handicraft blue collars	24.92	23.96
62. Qualified industrial workers	16.68	14.89
56. Individual service workers	7.67	8.06
55. Commerce and retail occ.	13.76	17.11
54. Clerical workers	19.02	17.21
53. Security occ.	0.13	0.07
Part-time status	0.11	0.11
Tenure at plant (days)	2,367	2,205
Age	40.29	40.20
Worker's characteristics - Untargeted moments		
Gender	0.66	0.64
Average yearly gross earning (€)	24,003	23,958
Average gross hourly wage (€)	14.59	14.66
Tenure at firm (days)	2,693	2,532
Tenure at job (plant × occ., days)	1,492	1,509
Panel B: Workers from above - Layer 3		
# unique ID	526	1,044
Worker's characteristics - Targeted moments		
38. Engineers and technical managers	47.53	47.60
37. Admin. and commercial managers and senior staff	50.95	49.95
34. Legal and scientific professions	1.52	1.15
Part-time status	0.05	0.05
Tenure at plant (days)	2,315	2,056
Age	44.20	43.55
Worker's characteristics - Untargeted moments		
Gender	0.76	0.76
Average yearly gross earning (€)	64,027	69,023
Average gross hourly wage (€)	35.29	38.46
Tenure at firm (days)	2,901	2,720
Tenure at job (plant × occ., days)	1,331	1,331

Note: This table reports sample balancing summary statistics of worker-level outcomes in the context of a fragmentation of Layer 2 occupations. A plant is fragmenting an occupation if the last worker in this occupation disappears from the plant's labor force at τ, and no one is re-hired in this occupation up until $\tau + 2$. The fragmented occupation must represent at least 10% of the place workforce between $\tau - 2$ and $\tau - 1$. The fragmenting plant's workforce excluding the fragmented occupation must not decrease by more than 10% between $\tau - 1$ and τ. Control plants are found within the same 1-digit industry code and *région*, the same size decile and the same quartile of total payroll distribution at $\tau - 2$. Treated and control workers are identified within these matched plants pairs, with at least two years of tenure at the plant. I impose that they are employed in the same layer between $\tau - 2$ and τ, the same occupation code at time τ, and have the same part-time status.

Table 3.6 reports summary statistics of treated and control units at the worker level in the context of a fragmentation of Layer 2 ("retained workers"). The share of unqualified jobs is slightly over-represented in the group of treated workers from Layer 1, but the sample balancing on other demographics and earnings is good for both treatments. While I am matching tenure at the job fairly closely, treated workers have systematically more days of tenure at both the plant and the firm.[53]

3.4.3 Empirical framework

At the plant level, I estimate an empirical model of of the following form:

$$Y_{ut} = \sum_{k=-4}^{k=10} \delta_k^T \mathbb{1}\left[t = \tau + k\right] \times F_{u,l(\tau)} + \sum_{k=-4}^{k=10} \delta_k^{NT} \mathbb{1}\left[t = \tau + k\right] + F_{u,l(\tau)} + \gamma_{m(u,\tau-2)} + \varepsilon_{ut} \tag{3.1}$$

where Y_{ut} is an outcome of plant u at time t, $F_{u,l(\tau)}$ is an indicator that the plant is a treated plant fragmenting an occupation of layer l at time τ, $\mathbb{1}\left[t = \tau + k\right]$ indicates that a fragmentation event occurred k years in the past (or will happen in k years in the future) relative to event year τ, γ_t is a calendar year fixed effect and $\gamma_{m(u,\tau-2)}$ is a match group fixed effect, which ensures that I am estimating the effect of my event only within a group of matched treated and control plants. The former only controls for the aggregate business cycle. Standard errors are clustered at the match level.[54] I omit the year $\tau - 2$ (two years prior to the event), so that each δ_k coefficient captures the difference in the outcome variable y_{ut} between a treated and a control plant relative to the difference at $t^* = \tau - 2$. Implicitly, this amounts to assuming that a fragmentation event starts at time $\tau - 1$ and is completed at time τ.

[53] I present summary statistics of displaced workers from Layer 1 whose occupation is fragmented by their employing plant in Panel C of Table C3 in Appendix C. The sample is very small (only 138 treated workers and 242 controls), which I attribute not to the lack of events in the economy but to the difficulty of tracking such workers in my panel of individuals. I find that 33% of the identified displaced workers are employed as unqualified production worker one year prior to their displacement.

[54] Two-way clustering at the county × 3-digit industry level, or clustering at the firm level yield similar standard errors.

A recent strand of the econometrics literature has emphasized a number of identification and interpretation issues that arise when using the timing of the treatment to identify a treatment effect. By using a matched control group that is never treated, the specification in equation (3.1) does not suffer from identification issues that arise in conventional event-study designs using never-treated units (Borusyak and Jaravel 2017)[55] or in difference-in-differences designs with staggered timing (Goodman-Bacon 2018). In specification (3.1), identification comes solely from differences between always- and never-treated units within a narrow matching group, and not from units coming in and out of treatment.

At the worker level, I estimate the following empirical model:

$$y_{it} = \sum_{k=-4}^{k=6} \delta_k^T \mathbb{1}\left[t = \tau + k\right] \times F_{u,o(\tau)} + \sum_{k=-4}^{k=6} \delta_k^{NT} \mathbb{1}\left[t = \tau + k\right] + F_{u,o(\tau)} + \gamma_i + \varepsilon_{it} \quad (3.2)$$

where y_{it} is a worker's career outcome at time t, $F_{i,o(\tau)}$ is an indicator that worker i is a treated worker in occupation o at the time of the fragmentation event τ, $\mathbb{1}\left[t = \tau + k\right]$ indicates that a fragmentation event occurred k years in the past (or will happen in k years in the future) relative to event year τ[56], and γ_i is a worker fixed effect. Standard errors are clustered at the individual level.

The key point of the narrative around the fissured workplace is that IJL fragmentations result in workers finding themselves in specialized workplaces. To validate my empirical design, I therefore first estimate equation (3.2), using as outcome y_{it} employer-level variables describing a worker's IJL. I focus on the length of treated workers' current IJL (how many layers) and its depth (what type of layers). I measure the latter by the inverse span of control that workers face (the number of "managers"

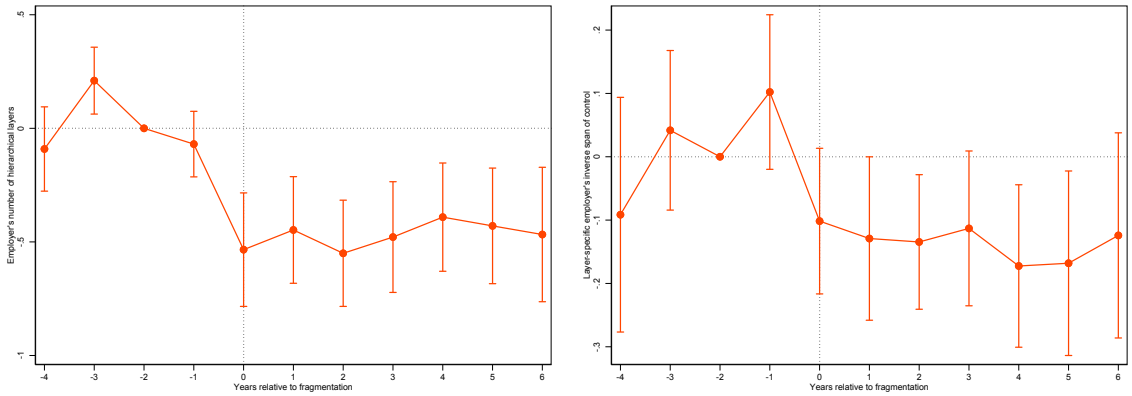
[55] The key issue emphasized in this paper, and immediately related to my design, is that it is impossible to identify the linear component of the path of pre-trends and dynamic treatment effects in the presence of unit and time fixed-effects. Unit fixed-effects are crucial in estimating the treatment effect without my estimates accounting for composition effects.

[56] While I observe plants for long periods of time, the average worker in my panel can only be observed for ten years. As a result, I reduce my event study window in the worker-level analysis.

per worker in the employing plant).[57] Average estimated effects on the whole post-event period are reported in Tables D3 (for "retained workers") and D4 (for "displaced workers") of Appendix D.

Figure 3.4: Employer's structure of displaced workers

(a) Number of layers in-house (b) Number of managers per worker



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of a Layer 1 worker's own occupation on the subsequent employer's number of in-house hierarchical layers (Fig. 3.4a) and inverse span of control (Fig. 3.4b), according to specification (3.2). A displaced worker is defined as a worker who was employed in occupation o of Layer 1 in plant f at time $\tau - 1$ and who leaves that employer at τ upon fragmentation of occupation o by plant f (see Section 3.4.1). For each treated worker I find a counterfactual worker employed in a counterfactual plant (matched on region, industry, size, payroll and employment growth as explained in Appendix C) in the same occupation o and in the same 15-year age-bin at time $\tau - 1$. A worker's inverse span of control is defined as the ratio of workers employed in the layer immediately above hers in her current employer's hierarchy, over the number of workers employed in her layer. 95% confidence intervals clustered at the individual level are displayed.

Figure 3.4 reports the estimated coefficients δ_k^T of Equation (3.2) when y_{it} is the number of layers in-house (Fig.3.4a) and the number of managers in Layer 2 per worker employed in Layer 1 (Fig. 3.4b) for displaced workers from Layer 1. I focus on displaced workers to assess whether or not these displaced workers who remain employed following fragmentation do move into more specialized organizational struc-

[57] This corresponds to the ratio

$$\frac{N_{ul+1t}}{N_{ult}}$$

, where N_{ult} is the number of workers employed in layer l in plant u at time t, for a worker employed in layer l.

tures.[58,59] By definition of the treatment, displaced workers who remain employed at the time of the fragmentation of their occupation move to a different employer. On impact, I find that the average number of in-house layers in this new employing plant declines by as much as 15% relative to the worker's initial employer. This decline is persistent, as shown in Figure 3.4a. Figure 3.4b reveals that displaced workers also experience a strong decline in their average inverse span of control. On impact the number of managers per worker that these displaced workers face in their new employing plant decreases by a staggering 75%. On average, between τ and $\tau + 6$ displaced workers from Layer 1 occupations find themselves in plants with significantly fewer managers per worker (-56%) than control workers relative to the previous employer.

These results show that the identified events have a long-lasting effect on the shape of individual workers' IJLs. In particular, the strong decline in the number of managers per worker suggests that treated workers experience a significant reduction in opportunities for internal mobility, in line with the fissured workplace narrative.

3.5 Fragmentation and plants' performance

3.5.1 A growth inducing event

Since A. Smith 1776's pin factory example, division of labor has been associated with productivity gains. In firms' organizational models, the division of production into several "teams" or "layers" is the result of a cost minimization problem. A deeper division of labor is associated with an optimal balance between fixed and marginal costs resulting in a decrease of average cost and an increase in productivity.[60] Models of production fragmentation emphasize the productivity gains associated with both

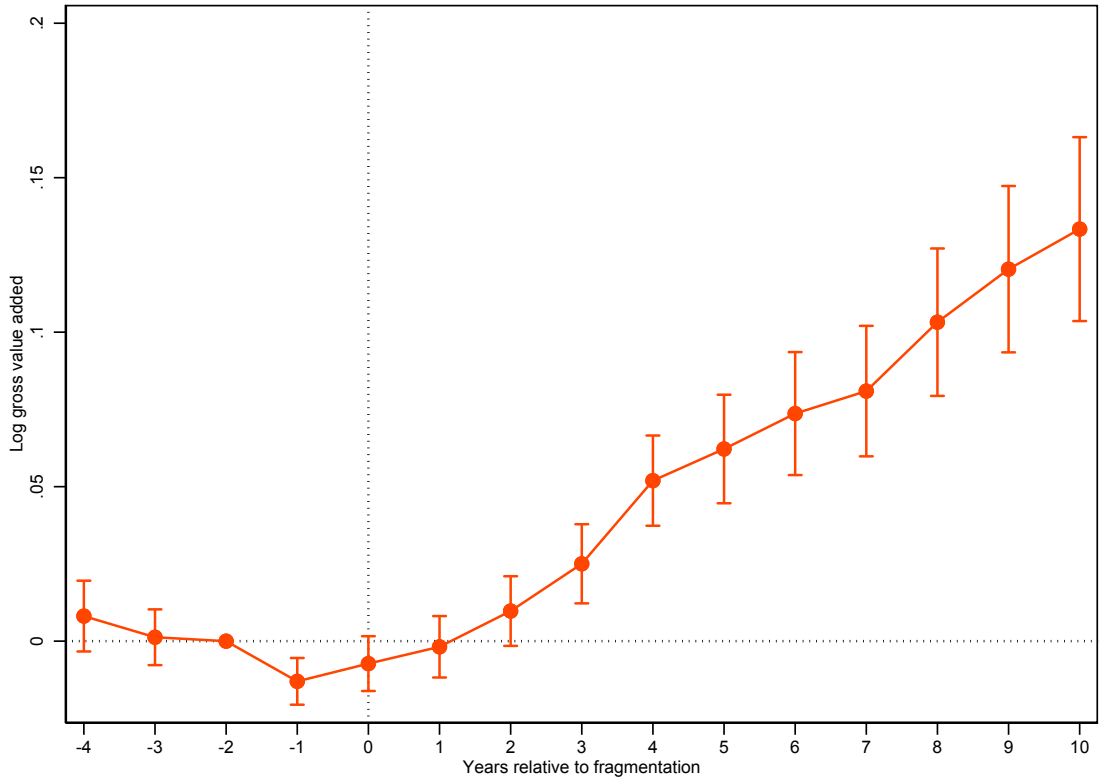
[58] I do not impose that workers identified as displaced due to a fragmentation event move to a specialized employer, nor in fact that they remain employed.

[59] Figure C5 in Appendix C confirms these qualitative results for retained workers.

[60] In particular, in models such as those developed in Chaney and Ossa 2013 and L. Caliendo and Rossi-Hansberg 2012, productivity is measured as output per worker.

cost savings (Grossman and Rossi-Hansberg 2008), and with returns to specialization (Humlum 2020, Grossman and Rossi-Hansberg 2012, Akerman and Py 2014, Antràs and Helpman 2004). I explore the empirical counterpart of these results. I show that IJL fragmentations are associated with growth-inducing events manifesting in an increase in value added and productivity, as well as strong employment growth.

Figure 3.5: Plant-level value added



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's log gross value added evaluated at factor prices, according to specification (3.1). For each fragmenting establishment, I find a control plant by matching on three-digit industry code and region, deciles of size at $\tau - 2$, quartiles of total payroll at $\tau - 2$, and annualized growth rate of employment, and of the ratio of Layer 2 workers over Layer 1 workers between $\tau - 4$ and $\tau - 2$. For a more detailed definition of a fragmentation, see Section 3.4.1. 95% confidence intervals clustered at the match level are displayed.

Figure 3.5 reports the coefficients δ_k^T from estimating Equation (3.1) with log gross value added measured at factor prices as outcome.[61] The estimates exhibit a

[61] Sales revenue, value added, expenditures and other financial variables from my analysis are only available at the firm level, not at the level of the plant. 60% of my establishments in the

strong monotonic increasing pattern starting from $\tau - 1$. I estimate that these events are associated with a significant 4.19% gain in gross value added over ten years as reported in Table 3.7, with gains culminating at 13.3% ten years out.

Table 3.7: Average effect of fragmentation events on plants' outcomes

	Log VA	Log Sales	Log unit variable costs	Log MPF	Log employment
Post $\times$ F_{ut}	0.0419***	0.0450***	0.0186**	0.0196**	0.0449***
	(0.0050)	(0.0052)	(0.0077)	(0.0084)	(0.0035)
Mean at $\tau - 2$	6.610	7.852	-1.392	-2.345	3.08
Adjusted R^2	0.5528	0.5692	0.2766	0.3559	0.6467
Plant $\times$ Year	943,056	952,489	954,108	942,810	1,019,098

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on establishment-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.5 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. SEs are clustered by matching groups id. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

The monotonic increase of value added between $\tau-1$ and $\tau+10$ mirrors an increase in sales revenue. I estimate a 13.6% gain in sales revenue after ten years in plants fragmenting Layer 2.[62] I test the presence of a cost-saving motive for fragmentation

matched sample are single-establishment firms. I estimate separately Equation (3.1) on the sub-sample of single-establishment firms in Appendix C. In the main specification, the outcomes of multi-establishment firms are attributed to plants based on their employment weight in the total employment of the parent firm. Sales and value added results are robust to restricting attention to single-establishment firms, regardless of whether Layer 2 or Layer 1 is fragmented (Figure E3). This is not true about productivity estimates.

[62]Figure D1a in Appendix D reports the dynamic difference-in-differences. After 10 years, the gain in sales revenue is a significant 14.5%.

in order to understand if the gain in value added is also driven by cost reductions.[63] Column (3) of Table 3.7 reports the average post-event estimates of Equation (3.1) when the outcome Y_{ut} is log unit variable cost.[64] It increases monotonically between τ and $\tau + 10$, and reaches a peak at $\tau + 5$ with a 5.97% increase relative to non-fragmenting plants. Taken together, these results confirm that the fragmentation of IJLs is associated with an increase in high value added generating production, but do not support the idea of a cost-saving incentive driving these reorganizations.

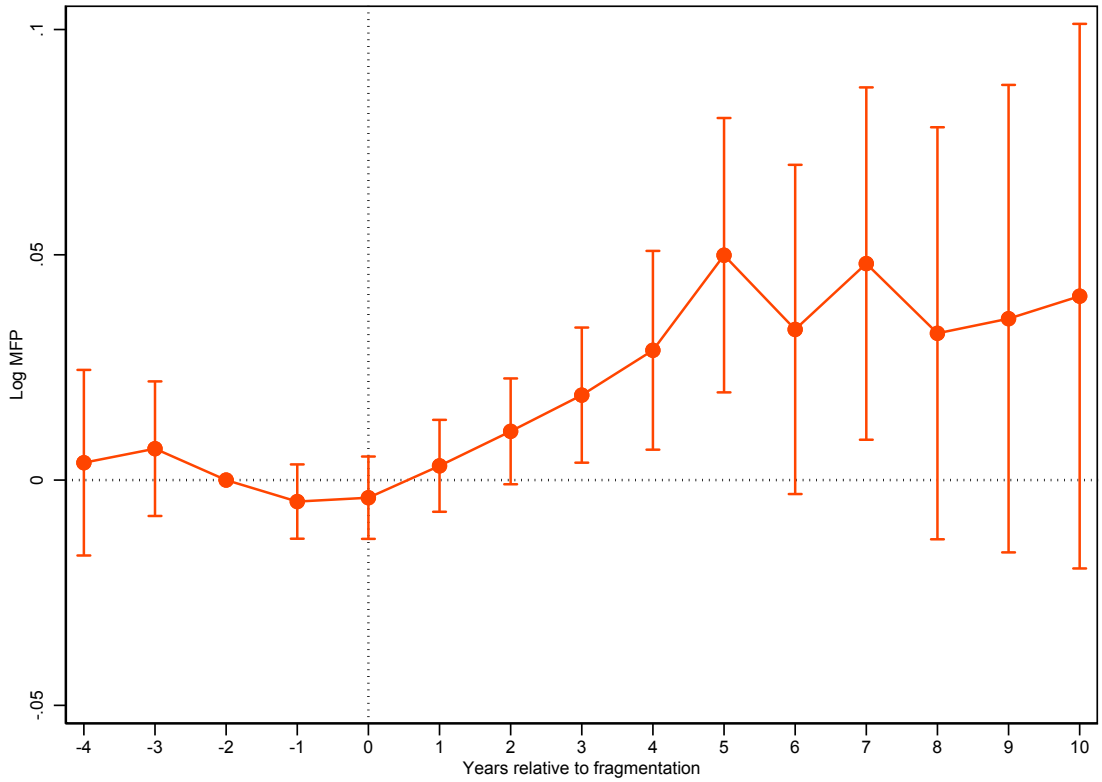
I then assess whether a plant's reorganization is associated with productivity gains. Figure 3.6 reports estimates of Equation (3.1) when the outcome Y_{ut} is multi-factor productivity, measured as the log ratio of gross value added at factor costs over total variable costs. Fragmentation decisions are associated with a significant increase in productivity. Five years after the fragmentation, multi-factor productivity has risen by as much as 4.77%. The average effect (Column (4) of Table 3.7) is estimated to be a significant 1.96% increase in multi-factor productivity.

The fragmentation of internal job ladders is usually associated with outsourcing and cost saving motives. I find that in plants fragmenting their IJL, there is in fact an increase in unit cost associated with a substantial increase in value added relative to non-reorganizing plants, suggestive of a focus on "core competencies" (or highest value-added generating activities).

[63] In their model, Grossman and Rossi-Hansberg 2008 develop a theory of trade in tasks according to which the firms facing lower outsourcing costs obtain a productivity gain due to the cost-saving effect of offshoring. They show that this effect is isomorphic to (low-skilled) labor-augmenting productivity, and would be consistent with a positive employment effect similar to the one I document below. The wage fairness literature as developed initially by Akerlof and Yellen 1990 and adapted to the specific context of international trade by H. Egger and Kreickemeier 2012 suggests similarly that fragmentation of non-essential activities at the plant level may be motivated by a need to compress within-plant wage distributions. I find, however, at the establishment level that wage variance seems in fact to increase in response to a fragmentation event. This would be at odds with the wage compression motive story.

[64] Unit variable cost is measured at the firm level as the sum of total wage bill, non-financial capital depreciation, intermediate input expenses and other production-related expenses. I attribute the plant level unit cost based on the employment share of a plant in the firm. See Figure D1b for the dynamic estimates.

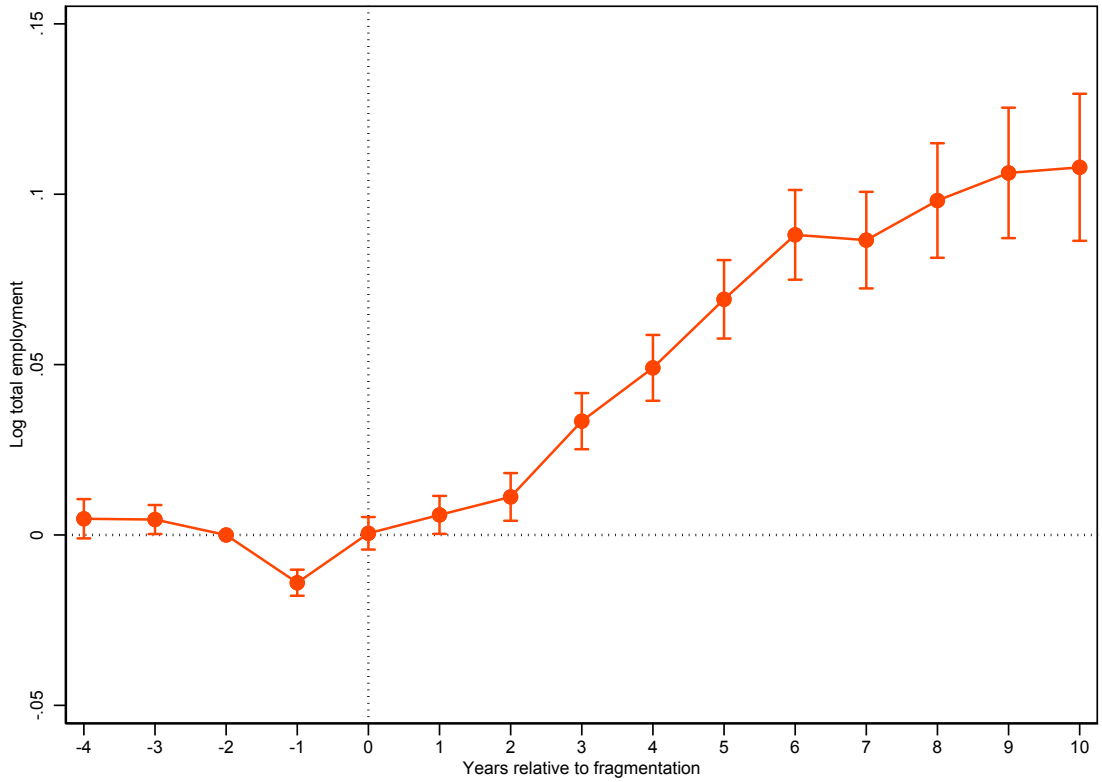
Figure 3.6: Plant-level multi-factor productivity



This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's multi-factor productivity, according to specification (3.1). A plant's MPF is measured as the ratio of gross value added over total variable costs. For details about the matching procedure, see Note of Figure 3.5 and Appendix C. 95% confidence intervals clustered at the match level are displayed.

To understand the extent of the plant's expansion at the time of its reorganization, I now turn to employment effects. Figure 3.7 plots the coefficients δ_k^T from estimating Equation (3.1) with log employment as the outcome Y_{ut}. The figure illustrates the fact that employment layoffs due to the fragmentation event commence one year prior to the total disappearance of the occupation, in line with the event timing described in Section 3.4.3. At year $\tau - 1$ log employment falls significantly by 0.014, but at the time the fragmentation is completed, employment has reverted to a positive trend. Between τ and $\tau + 2$, in which plants are required not to re-hire anyone from the fragmented occupation, employment increases by a significant 1.1% relative to non-

Figure 3.7: Plant-level log employment

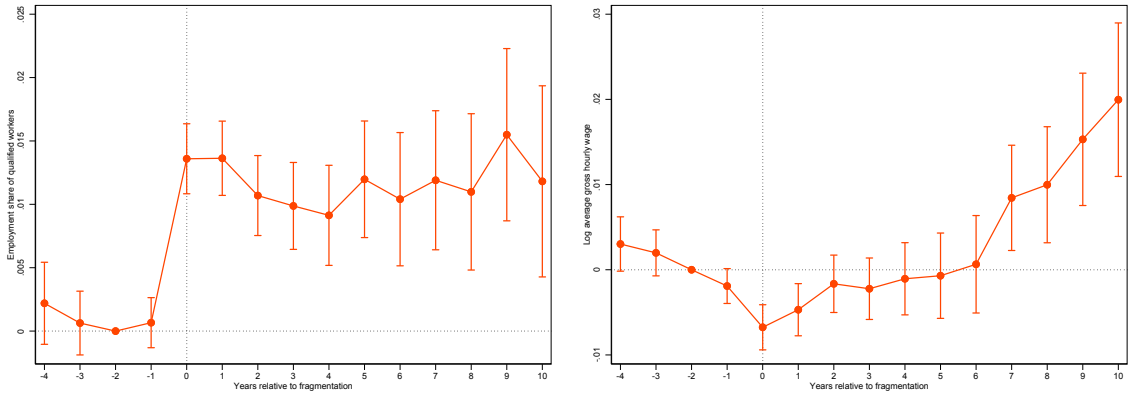


Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's log employment, according to specification (3.1). For details about the matching procedure, see Note of Figure 3.5 and Appendix C. 95% confidence intervals clustered at the match level are displayed.

fragmenting plants. Once this constraint is lifted, log employment exhibits a strong increasing pattern.[65] Ten years out, employment in the treated plant has increased by 11% relative to non-fragmenting plants between $t-2$ and $\tau+10$. The estimated mean effect represents a 4.49% increase in employment due to fragmentation.

Figure 3.8: Plant-level composition effects

(a) Employment share of qualified workers (b) Log average gross hourly wage in the plant



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's average hourly wage (Fig. 3.8b) and share of qualified workers (Fig. 3.8a), according to specification (3.1). A plant's share of qualified worker is identified as the employment share of two-digits occupation codes 21, 22, 23, 34, 37, 38, 47, 62 and 65. For details about the matching procedure, see Note of Figure 3.5 and Appendix C. 95% confidence intervals clustered at the match level are displayed.

3.5.2 Employment composition effects

I find robust evidence that plants fragmenting their IJL are expanding in terms of employement. How is this expansion achieved? In order to explore the composition effects behind the strong positive employment effect documented above, Figure 3.8 reports the estimates of Equation (3.1) with employment share of qualified workers and log average gross wage respectively as outcomes.[66] Figure 3.8a reveals that while the initial layoff phase of the fragmentation process at $\tau - 1$ is not associated with any significant change in the employment share of qualified workers, I estimate a significant jump in this share by 0.014 at τ. The average increase in the share of qualified workers in the plant's employment represents a 2.22% increase relative to

[65] I discuss in more detail in Section 3.5.3 the robustness of this result. In particular, I check that the change of slopes at $\tau + 2$ is not entirely driven by plants re-hiring the same occupation they just fragmented.

[66] I define as qualified workers workers employed in occupation codes 21, 22, 23, 34, 37, 38, 47, 62 and 65, all occupation codes associated with some form of specialized technical training according to the job title. This definition is not collinear with the definition of any of the hierarchical layers.

the $\tau - 2$ share of qualified workers. Figure 3.8b sheds some more light on how these composition effects translate in terms of wages. On impact, the average hourly gross wage of workers significantly decreases. This effect subsides after a few years, and in the long run the average gross hourly wage increases and is 2% higher at $\tau + 10$. These two pieces of evidence are consistent with a theory of businesses focusing their workforce on specialized activities with higher skills and/or technical requirements.

The picture depicted here reveals that following a plant's adoption of a fissured structure, plants' performance is increasing. The events are associated with a specialization of these plants in their highest-value added generating activities (or "core competencies"), in particular through increased (external) employment of specialized workers both at the bottom and the top of the internal job ladder.

3.5.3 Robustness

In this section, I discuss the robustness of my main results to various ways of specifying the fragmentation event considered, and to the empirical specification. All robustness results for plant-level outcomes can be found in Appendix E.

Robustness to the event definition

Several concerns arise over the capacity of my events to describe true reorganization events. The first concern is that most of the effects estimated are driven by the no-rehiring constraint imposed by condition (3) in the definition of an occupation's fragmentation. I therefore consider how employment in the specifically fragmented occupation evolves after the fragmentation event in Figure C1b. There is a significant pre-trend, suggesting that - in line with the argumentation in Section 3.4.2 - occupation-specific exposure is a predictor of subsequent fragmentation. Beyond the $\tau + 2$ no re-hiring constraint, employment in the fragmented occupation increases relative to the period τ to $\tau - 2$, by about 7p.p. The average effect, however, re-

mains large and significantly negative, and the point estimate at $\tau + 10$ still measures a 27% decline in employment of that specific occupation compared with before the fragmentation. I then repeat the analysis on a larger sample of matched plants, where fragmentation is defined as before absent condition 3 (no re-hiring constraint post-fragmentation). Average effects of this robustness check are presented in Appendix E and reveal that all the results are robust to this constraint, although the magnitudes estimated suggest some form of attenuation bias.

A second potential issue to be addressed is that the events identified are transitory. In Appendix C, I further describe the employment effects of a fragmentation event by considering log employment of each specific layer within a plant (Figure C3-C4). In plants fragmenting an occupation from Layer 2, the total employment in that layer decreases on average by 17% over the next ten years. The corresponding estimated average increase in Layer 1 employment is 9.69% and long-lasting, and employment in Layer 3 increases by 4.30% over the period τ to $\tau + 10$. I take this as evidence that my events do identify a permanent change in the workforce composition of the plant.

A third concern, directly related to this, is that the fragmentation of Layer 2 is driven by internal promotions of all the workers of occupation o from Layer 2 to Layer 3, as could be suggested by the spike in log employment of Layer 3 on impact in Figure C4. Note that such a change could bias some of the results regarding the share of qualified workers and average wages upwards. If that were the case however, total employment should not respond upon fragmentation, which is not consistent with the employment decline at $\tau - 1$, nor the small but significantly positive increase of log employment at $\tau + 1$. Furthermore, in the context of the French classification, a 2-digit occupation code such as those I used groups on average more than forty 4-digit occupation codes, while wage variance within layers remains low (cf. Appendix A). Job title re-labeling and implicit promotions are therefore less likely.

Robustness to the type of fragmentation

My results are also robust to the type of occupation fragmented; and to considering single-establishment firms.

Figures E1-E2 in Appendix E show that all the main results estimated when occupations from Layer 2 are fragmented are of similar magnitude when considering plants fragmenting an occupation from Layer 1. This confirms the fact that the growth in value added and productivity I estimate are not confounded with pure workforce composition effects.

While increases in sales revenue, value added and unit cost are also present in single-establishment firms (as reported in Appendix E), the productivity gain estimated in Section 3.5.1 is not robust to restricting attention to single-establishment firms. In fact, for these plants I observe a decrease in multi-factor productivity, while labor productivity remains constant, suggesting that while returns to specialization in the form of high value-added generating production is generalized across fragmenting plants, productivity gains only accrue to multi-establishment firms capable of using between-plant factors' reallocation.

Robustness to clustering and matching

Table E2 reports estimates of the average effect of a reorganization on plants' outcomes for various clustering choices. The first row replicates the results Table 3.7, when standard errors are clustered at the match level. In the second and third rows, I cluster the standard errors at the individual plant level, and at the industry $\times$ region level respectively. The statistical significance of the main results is preserved.

I then test the sensitivity of the estimates to the matching procedure and implicit weighting scheme. To verify the parallel trends assumption in these robustness checks, Appendix E reports the graphical results. First, instead of matching each treated unit to all possible control units, I randomly choose one single control plant per

treated one. This changes the number of matched pairs, but does not significantly alter the main finding. Second and finally, I reduce the set of matching variables to level variables only (county and industry, size decile and total payroll quartile). The parallel pre-trends are robust for value added and employment in particular.

3.6 Fragmentation and workers' careers

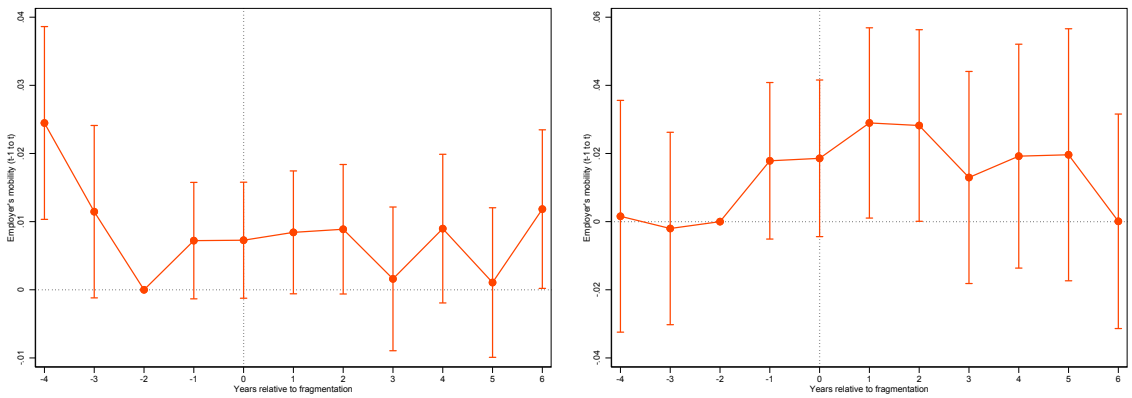
What is the effect of this fissured workplace on workers? The plant-level results imply that there are potential gains from such reorganization due to returns to specialization. Understanding how the generated extra value added is shared with workers is key in assessing the fissured workplace narrative on workers' careers. In this section I describe the effect of IJL fragmentation events on worker-level outcomes.

3.6.1 Effect on employer's mobility

The main line of argument in the fissured workplace narrative is that workers employed by specialized employers suffer from decreased upward mobility and declining job security. In order to assess the empirical relevance of this point concerning decreased job security and hence higher turnover, I first consider the response of workers' mobility across employers to reorganization events. In models that explicitly consider within-plant job ladders (Kramarz, Postel-Vinay, and Robin 2014, Pastorino 2015), plants with longer IJLs offer a better allocation of workers' ability to tasks and better opportunities for upward mobility, which increases workers' turnover between fissured structures towards complete pyramids. In this framework, we would expect fragmentations to increase workers' mobility across firms. Conversely, in job search models across heterogeneous firms, larger organizations with higher current sales revenue attract workers and increase their job turnover (Bagger et al. 2014). In this framework, we would expect worker turnover from specialized organizations to decrease.

Figure 3.9: Employer mobility of stayers

(a) Workers "below" (Layer 1) (b) Workers "above" (Layer 3)



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the yearly probability of changing employer (firm) for workers employed in Layer 1 (Fig. 3.9a, "retained below") or in Layer 3 (Fig. 3.9b, "retained above"), according to specification (3.2). A retained worker "from below" is defined as a worker who is employed in occupation o of Layer 1 in plant f at time τ upon fragmentation of an occupation from Layer 2 by plant f at time τ (see Section 3.4.1). A retained worker "from above" is defined as a worker who is employed in occupation o of Layer 3 in plant f at time τ upon fragmentation of an occupation from Layer 2 by plant f at time τ (see Section 3.4.1). For each treated worker I find a counterfactual worker employed in a counterfactual plant (matched by region, industry, size, payroll and employment growth as explained in Section 3.5) in the same occupation o and in the same 15-year age-bin at time $\tau - 2$. 95% confidence interval clustered at the individual level are displayed.

Figure 3.9 reports the coefficients δ_k^T of Equation 3.2 where the outcome y_{it} is the probability for an individual i to change employers between $t-1$ and t, for retained workers in plants fragmenting an occupation of Layer 2. Despite a matching procedure imposing a two-year tenure at the fragmenting plant of treated and control workers, it is immediately clear from Figure 3.9a that workers from Layer 1 in plants fragmenting occupations of Layer 2 are initially more mobile than their counterparts, suggesting some form of selection in this group. Pre-trends for workers employed in L3 on the other hand are parallel.

Retained workers at the bottom of the internal job ladder do not appear to be significantly more or less mobile than their counterparts in non-fragmenting organizations. The point estimates of the dynamic specification are not significantly different

from zero. The average effect between $\tau + 1$ and $\tau + 6$ is insignificant and negative (-10% relative to average mobility rates in the pre-period) suggesting if anything a slight decrease in mobility across firms for workers "from below".[67] Retained workers "from above" on the other hand appear more mobile than their controls, with an estimated average effect of a 42% increase in mobility across firms.

This suggests that workers experiencing a fragmentation of their IJL, and in particular workers who see their upward opportunities decrease, do not tend to move more often to different employers (whether by choice or by obligation) in the medium-run. On the other hand, fragmentations are associated with increased turnover in management.

I find stronger effects for displaced workers. After the initial displacement spike at time τ, points estimates suggests that displaced workers are on average twice more likely than their non-displaced counterparts to move between employers in the three years following the fragmentation event. The average effect over the five years following the event is however insignificantly different from zero.[68]

3.6.2 Effect on occupational mobility

While the weak employer mobility response of workers at the bottom of the ladder documented above does not support claims of workers' declining attachment to their employer, it does not reflect their opportunities for upward mobility either. I therefore now estimate in Figures 3.10-3.11 the effect of an IJL fragmentation on a worker's probability of being promoted one layer up.

It should be remembered that in the definition of the fragmentation I consider, I do not impose that the entire Layer 2 disappears from the employing plant workforce, as this event is too rare in my data. What I do impose, however, is that this layer

[67] I find, however, a significant 31% increase in within-firm between-plant mobility for workers "from below", conditional on their being employed in a multi-establishment firm at the time of the fragmentation event. Details are given in Appendix D.

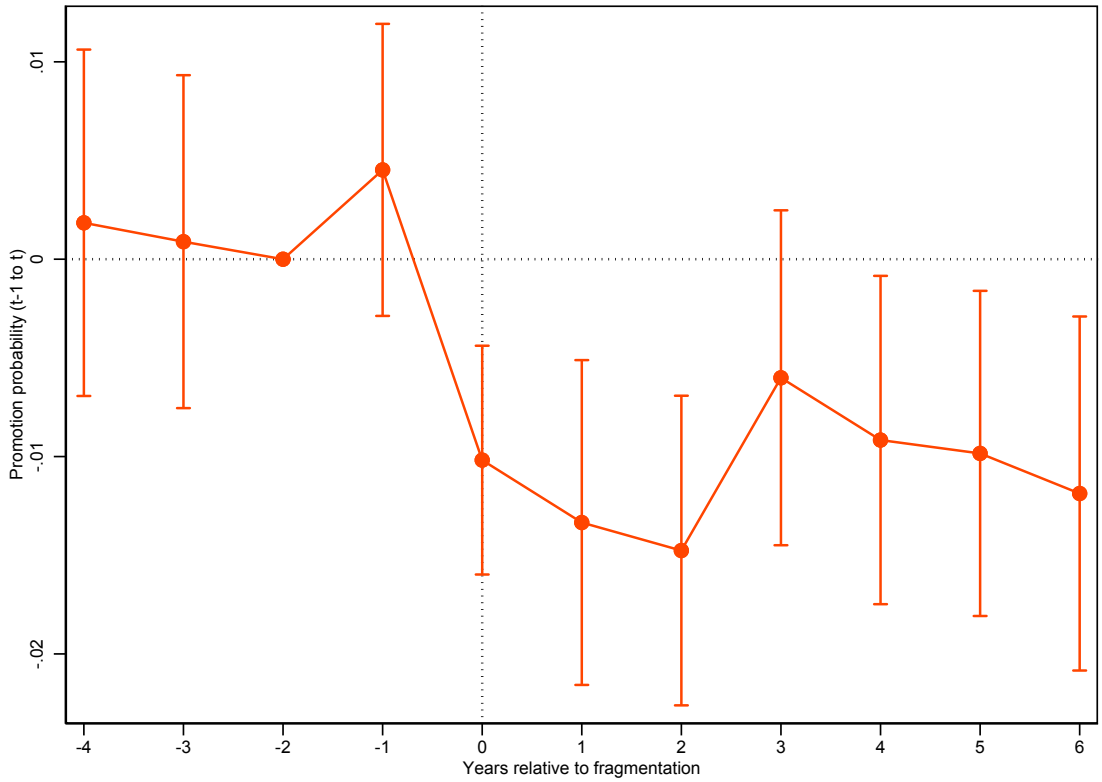
[68] See Figure D7, and more generally Appendix D for graphical results for displaced workers.

experiences a significant drop in employment due to the disappearance of one or several occupations in that layer. Personnel economics theory (Lazear and Rosen 1981, Lazear 1992, Gibbons and Waldman 1999) models the promotion process as the result of a job-assignment decision. Occupations are viewed as in Jovanovic and Nyarko 1997 as "stepping stones", where a career is a progression from simpler to more complex occupations. In this framework, whether or not these stepping stones exist is a crucial factor in determining the career path of a worker. These models often predict serial correlation between promotion opportunities, and a decline in promotion rates when workers' abilities prevent them from reaching the next step. Models focusing on the strategic equilibrium job assignment when learning is asymmetric between incumbent and external employers predict reduced turnover due to the informational rent detained by the incumbent employer (Waldman 1984, Greenwald 1986, Ricart I Costa 1988, Bernhardt 1995), and inefficient job assignment resulting in slower promotion rates. Both types of frameworks allow us to suppose that a fragmentation of the layer above a worker's current layer should have a persistent effect on her mobility.

Figure 3.10 reveals a strong effect of IJLs' fragmentations on retained workers "from below". On impact, workers employed in an entry-level job whose employing plant fragments an occupation in the layer immediately above see their probability of promotion decrease significantly by 105% between $\tau - 2$ and $\tau + 1$ relative to retained workers in non-reorganizing plants. Even after 6 years, their probability of being promoted remains at a significant 0.013 p.p. gap below that of control workers. The average treatment effect over the six years from the date of the fragmentation represents a significant 65% decrease in the yearly average promotion rate.[69] I further

[69]Decomposing this effect into a change in internal versus external promotion probabilities (Figure D2 in Appendix D and Table D5 in Appendix D) reveals that the bulk of this effect is driven by a combination of the lack of internal promotion opportunities, and no particular changes in employer mobility. Figure D4 shows that there is no increase in within-firm between-plant promotions either for workers employed in multi-establishment firms.

Figure 3.10: Promotion probability - Workers "below"



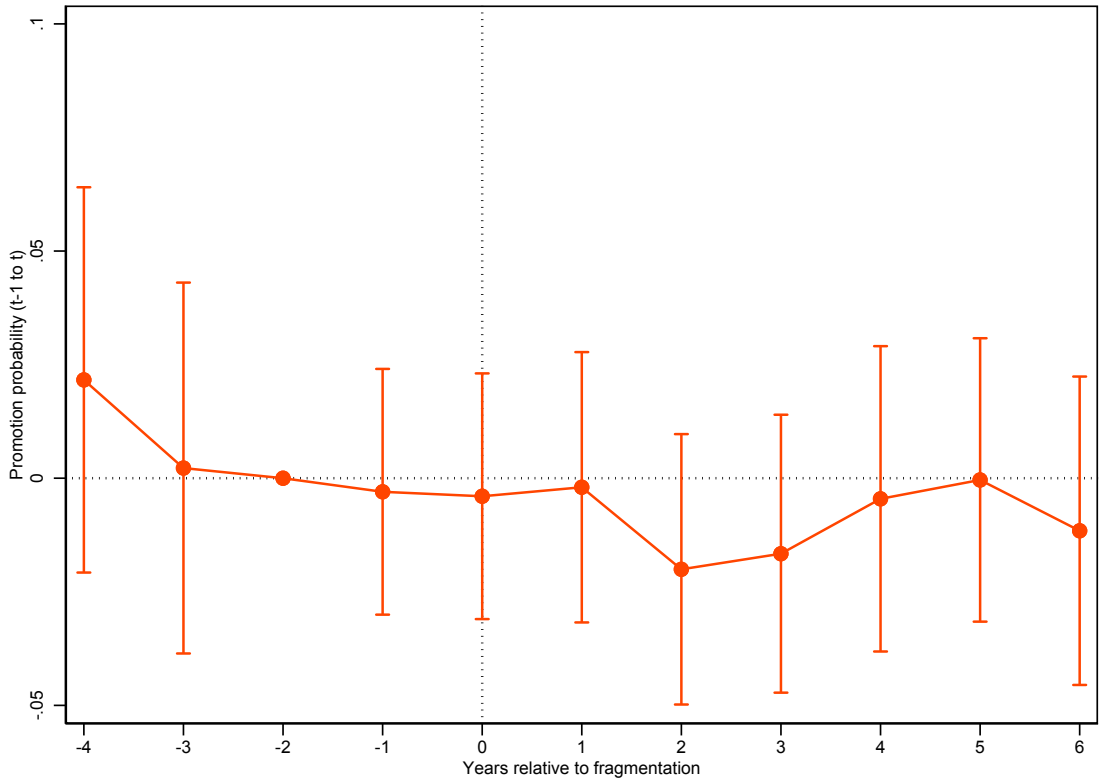
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on workers employed in Layer 1's subsequent probability of being promoted, according to specification (3.2). For a definition of "retained below" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.9. 95% confidence interval clustered at the individual level are displayed.

explore whether this decline in upward mobility is partially compensated by an increase in within-plant within-layer occupational mobility in Table 3.8.[70] On impact, I do find that within-layer occupational mobility increases by about 41% relative to $\tau - 2$ in comparison to non-treated workers. This effect however subsides as early as in $\tau + 1$. The average effect of a fragmentation of Layer 2 on retained workers in Layer 1 is in fact negative (although insignificant) and estimated as a 9% decline of the within-layer occupational mobility probability. This suggests that such a decline

[70] Graphical representations are presented in Appendix D

in opportunities for promotion is symptomatic of an overall decline in occupational mobility, and does not mask within-layer promotions that I could have mislabeled.

Figure 3.11: Promotion probability - Workers "above"



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on workers employed in Layer 3's subsequent probability of being promoted, according to specification (3.2). For a definition of "retained above" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.9. 95% confidence interval clustered at the individual level are displayed.

The effect of IJL fragmentation for retained workers employed in the layer above the one fragmented are unsurprisingly very different. Intuitively, these workers do not experience any changes in their opportunities for promotion. And indeed, I don't find any significant response in upward mobility of these workers to the reorganization event. The estimated mean effect between $\tau + 1$ and $\tau + 6$ is insignificantly different

from zero, suggesting that after the reorganization event these workers' opportunities for promotion are not significantly different from those of their control counterparts.[71]

I repeat the event-study analysis on the probability of promotion (Appendix D) for workers previously employed in Layer 1 and displaced due to a fragmentation of their occupation. I do not find significant effects of the fragmentation event on the relative promotion probabilities of treated workers. While they are more mobile across firms than similar workers not displaced during a reorganization, they are not more or less likely to be promoted in the process.

To summarize, the immediate effect of a reorganization is substantial in terms of occupational mobility for incumbent workers at the bottom of the ladder. For retained workers who experience a fragmentation of their promotion opportunities (occupations in the layer immediately above theirs), this translates into a long-lasting decline in promotion probability with no compensation through employer mobility or within-layer occupational mobility. This happens in particular despite employing reorganizing plants being on an upward trend. To some extent, these results confirm the negative narrative of the "fissured workplace" developed around workers at the bottom of the income distribution: working in a fissured workplace seems to interrupt these workers' careers. This does not appear to be true for displaced workers moving to plants specialized in low-skill occupations, for which I do not find significant mobility responses to a fragmentation event. For workers employed in the hierarchical layer above the one that is partially fragmented, the reorganization effect has no subsequent effects on upward mobility.

3.6.3 Effect on wages

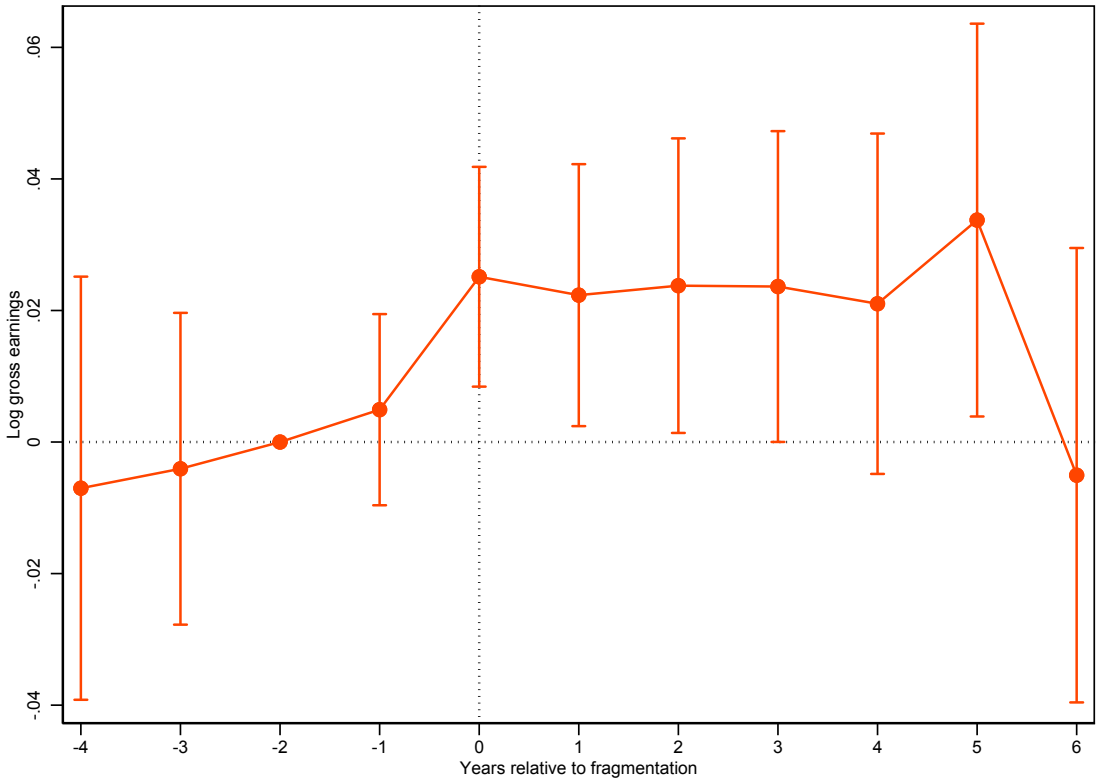
How do these fragmentation events reflect on the trajectory of workers' wages? The "fissured workplace" narrative emphasizes the fact that reduced opportunities for

[71] Panel B of Table 3.8 also confirms that there is no particular effect of the fragmentation on within-layer occupational changes.

upward mobility go hand-in-hand with lower wage growth. In internal labor market career models, current wages are tied to promotions.[72] A lack of mobility of workers across occupations, as is observed for retained workers, is associated with declining wage patterns. I confront this hypothesis with the data.

Figures 3.12 and 3.13 report the estimated coefficients δ_k^T of Equation (3.2) when the outcomes y_{it} is worker i's log gross (yearly) earnings for retained workers "from below" and "from above" a fragmented Layer 2.

Figure 3.12: Log gross earnings - Workers "below"



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on workers employed in Layer 1's log gross yearly earnings, according to specification (3.2). For a definition of "retained below" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.9. 95% confidence interval clustered at the individual level are displayed.

[72] In these models, wage gains and losses can occur through the learning and human capital accumulation process, irrespective of promotions or demotions. However, the theory predicts discrete jumps in earnings upon promotion.

I first focus on retained workers "from below". The matching procedure does not impose that treated and control workers lie on the same wage growth trend prior to the fragmentation event, but I find parallel trends nonetheless.[73] On impact, I estimate that workers hierarchically below the fragmented occupation at time τ see their gross earnings increase significantly by 2.5% relative to the control workers. This positive effect remains persistent and significant over time. Five years after the fragmentation of these workers' IJLs, the difference in log earnings between $\tau+5$ and $\tau-2$ remains at +3.3% (but is now only significant at the 5% level). The average treatment effect over the six years following a fragmentation event is significant and estimated at 2% (Table 3.8).

Figure 3.13 shows a very different wage effect of IJL fragmentation on retained workers "from above". On impact, these workers see their gross earnings decrease by 3.7% (significant at the 5% level) relative to counterfactual workers in the same position.[74] The subsequent point estimates are insignificant, which suggests that overall there's little effect of the reorganization on these workers wage.

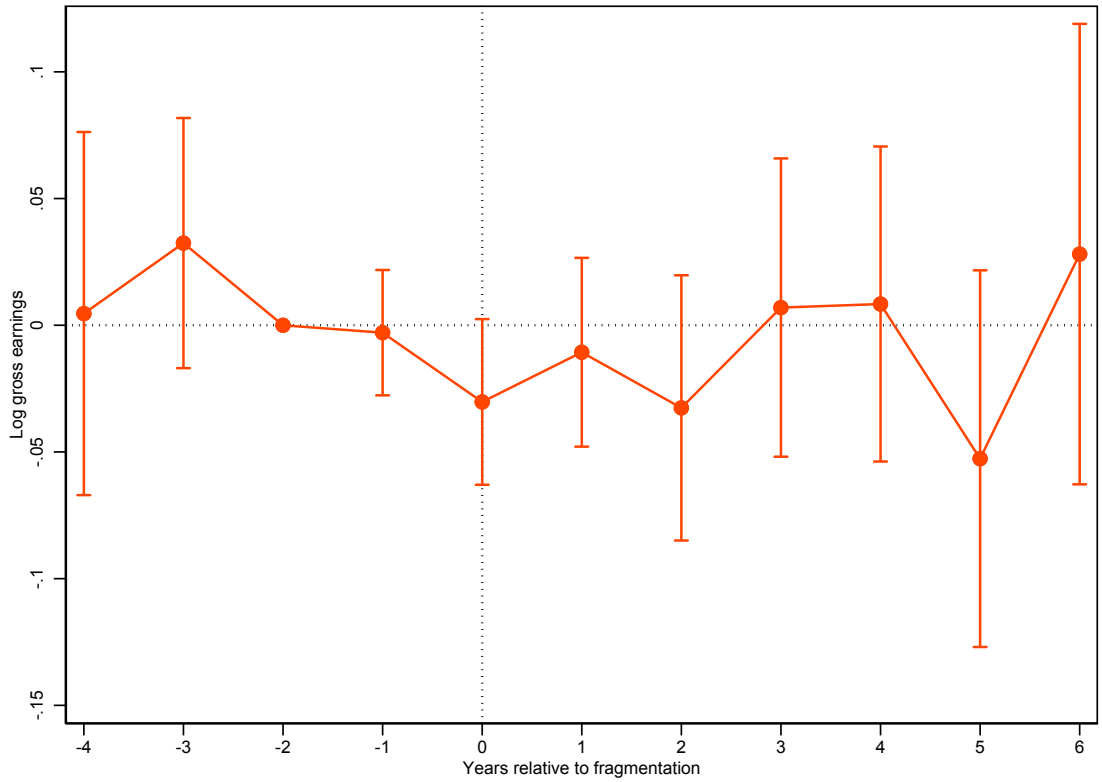
These wage responses are *a priori* surprising. Retained workers from Layer 1 see their promotion opportunities immediately decrease, while retained workers from Layer 3 are unaffected by the reorganization, which would be more consistent with a decline in L1 workers' wages and no response of L3 workers' wages. One possible explanation for such responses would be the presence of compensating wage differentials.[75] If a worker's income is tied to her ability to climb the ladder within a given plant, a hollowing-out of the hierarchy in response to a reorganization could lead to an increase in the worker's wage as a way of compensating her and immediately offset

[73] While the figure suggests that there might have been some increasing pre-trend for treated workers, the point estimates prior to the event are insignificant, and the slope of that pre-trend appears different from the increase observed at time τ.

[74] Recall that this estimate is relative: it does not imply a wage cut in absolute terms, only that these workers see their wage increase less than control workers.

[75] In Lamadon, Mogstad, and Setzler 2019 for example, workers' preferences across heterogeneous firms (or in my context, heterogeneous organizational structures) lead to compensating differentials in wages.

Figure 3.13: Log gross earnings - Workers "above"



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the log gross yearly earnings of workers employed in Layer 3, according to specification (3.2). For a definition of "retained above" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.9. 95% confidence interval clustered at the individual level are displayed.

the reduced appeal of a sparser hierarchy (and the resulting fall in the net present value of workers' future earnings). For retained workers "from above", the absence of changes in promotion opportunities would imply no response in terms of earnings, as estimated.[76] Alternatively, workers employed in fragmenting plants could benefit from the increase in value added documented in Section 3.5, which could lead to an increase in wages for all types of workers. The absence of significant wage increases for workers from above, and their increased turnover in the aftermath of the reorga-

[76] I estimate that retained workers "from above" are more than twice less likely to be demoted than controls workers, but I showed that they are also more mobile across employers. In a compensating differentials framework, the resulting wage earnings would be ambiguous.

Table 3.8: Average effect of fragmentation events on worker's outcomes

	Employer mobility	Promotion	Within-layer occ. switch	Log gross earnings
Panel A: Workers from "below"				
Post × $F_{f,o(\tau)}$	-0.0017	-0.0092***	-0.0052	0.0204**
	(0.0024)	(0.0019)	(0.0035)	(0.0083)
Mean pre-period	0.0299	0.0141	0.0570	9.96
Adjusted R^2	0.0223	0.0259	0.1162	0.4186
ID × Year	97,618	97,229	97,229	101,075
Panel B: Workers from "above"				
Post × $F_{f,o(\tau)}$	0.0160**	-0.0106	-0.0001	-0.0193
	(0.0073)	(0.0073)	(0.0122)	(0.0224)
Mean pre-period	0.0381	0.0257	0.0764	11.05
Adjusted R^2	0.0302	0.0097	0.1020	0.5881
ID × Year	14,535	14,488	14,488	14,930
Panel C: Displaced workers				
Post × $F_{f,o(\tau)}$	-0.0226	-0.00121	-0.0302	-0.1590
	(0.0146)	(0.0082)	(0.0269)	(0.1014)
Mean pre-period	0.0121	-0.00578	0.0948	9.410
Adjusted R^2	0.0707	0.0242	0.1015	0.4917
ID × Year	3,110	3,085	3,085	3,316

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 (respectively 1 in Panel C) occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.9 and I average the six post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 2 (respectively 1 in Panel C) at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by individual identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

nization, suggest that the rent-sharing process in the aftermath of the reorganization is unequal across workers depending on their position in the internal ladder, and becomes unfavorable for retained workers at the top of the ladder.

To explore further the two hypothesis of compensating differentials and changes in the rent-sharing environment of workers, I consider the earnings response of displaced workers. On impact, I estimate a significant decline in displaced workers gross earnings of 48.4% in the pre-fragmentation income relative to similar non-displaced workers (Appendix D).[77] Consistent with what is found in most studies on displaced

[77]For displaced workers, the dependent variable used includes imputed unemployment benefits. Based on the average French replacement rate of 40% of prior income, I attribute workers who appear to be unemployed for a maximum of two years (which represents the legal amount of time during which a worker can claim unemployment benefits) with an income equal to 40% of their last observed income. This substantially decreases the point estimate on impact, and the average effect of the entire post-period. I find a wage effect on displaced workers conditional on remaining

workers, the negative wage effect of a fragmentation is persistent, at least in the medium-run.[78] The average effect of fragmentation on displaced workers' wages in the six years following the event is negative (although insignificant) and estimated to represent a 15.9% decline in gross earnings.

The significant decline in displaced workers earnings is not consistent with compensating differentials. In their paper, Goldschmidt and Schmieder 2017 argue that it is highly likely that the bargaining environment of these workers changes drastically, making it difficult for outsourced workers to bargain for a share of specialized contractors' income. To some extent, this may also be true for the retained workers in fragmenting firms: workers at the bottom of the hierarchy who remain in these plants might be kept on for reasons that do not apply for Layer 1 occupations that can be outsourced to external suppliers or automated. This would be consistent with a plant-level increase in qualified workers (which include low-skilled specialized entry-level jobs as a group). In response to the workforce composition at the plant level, these workers may see their marginal contribution to plant's value added increase. Conversely, retained workers from above see their pool increase, and individual workers' marginal contribution to the plant's output decreases, along with their earnings. Taken together, these earnings results suggest that while there may be compensating differentials in fragmenting plants, the fissured workplace also brings about changes in workers rent-sharing environment.

3.6.4 Robustness

In this section I briefly discuss the robustness of my wage results. All robustness results on workers' outcomes can be found in Appendix E.

employed of -35.6% on impact. Note that this approaches the estimated effect of job loss due to firms' closure of a 30% decrease in earnings on impact, and an average 25% loss even six years later in Jacobson, LaLonde, and Sullivan 1993.

[78] Three years after the fragmentation of their occupation, I find that treated workers still experience a 42% decline in gross earnings relative to pre-event wages.

The wage increase of retained workers from the bottom of the IJL in reorganizing plants goes against the negative narrative surrounding specialized employers. One worry is that this is a statistical artifact: I have shown in the previous section that while promotion probabilities are negatively affected by IJL fragmentation events for the retained workers "from below", they nonetheless experience a strong increase in within-layer occupational mobility at the time of the event. It could be that the changes in job titles observed are not attributed to promotions according to my definition of a plant's hierarchy, while in reality they are a form of promotion. This concern would be particularly relevant if the occupation codes used to define occupational mobility were at a finer classification level, as discussed in Section 3.5.2. In Appendix D, I show that the timings of the increased occupational mobility and the wage increase in response to a fragmentation do not coincide. If they were to be associated, one should see a change in gross earnings at $\tau - 1$, which does not appear in my estimation.

Regarding the wage decline of workers at the top of the IJL, when testing the robustness of this result I utilize the fact that I also observe stayers from above when occupations from Layer 1 are fragmented. For these workers, I find, as depicted in Figure E10 in Appendix E that fragmentation events have a similar insignificant but negative impact on their gross earnings (the point estimate δ_0^T is -0.010). The mean effect for these workers over the six years following the event is estimated to be -0.00896, representing a 0.9% average earnings decline.

Finally, I test for the robustness of all my worker-level results to my clustering choices. Table E3 reports estimated average effects when standard errors are clustered at the match level rather than the unit level. The main results are maintained although standard errors are slightly greater.

These results nuance the fissured workplace narrative. Whereas the decline in upward mobility for workers at the bottom of the hierarchy was confirmed, I find

that the wage effects on retained workers do not match the common view of a wage decline for these workers. Contrary to a notion of within-firm wage polarization in favor of high-skilled workers, my results suggest that the fragmentation of internal job ladders has a positive earnings impact on retained workers in low-skill jobs, and a negative effect on retained workers in high-skill occupations. There is no overarching framework that would allow me to predict both worker mobility and wage responses to a fragmentation of internal job ladders. My results on employer mobility and promotions are consistent with a traditional theory of job assignment in the context of frictions on the external labor market. They do not, however, match the wage predictions that would derive from such a framework. Instead, I argue that wage responses to the fissured workplace are consistent with a change of bargaining power among workers, leading to substantial wage losses for "less essential" workers, and an inversion of bargaining power between retained workers "from below" and "from above" to the benefit of the former.

3.7 Conclusion

The implications of the "fissured workplace" are a major source of debate. I use comprehensive French micro-data to provide empirical evidence on this debate. I first propose a new measure of the occupational job ladder and show how it shapes plants' internal job ladders. I use this measure to identify the fragmentation of internal labor markets into fissured organizations and document changes in workers' working environment and careers. Whereas most prior research has focused on displaced workers, I focus on retained workers still employed in reorganizing plants at the time of the fragmentation. I use a matched difference-in-differences estimator to control for the non-random selection of plants into different organizational forms and the sorting

of workers to particular employers. My findings suggest that the implications of the fissured workplace are more nuanced than commonly thought.

As a motivating factor for my analysis of the fragmentation of internal job ladders, I document that young workers at the beginning of their career face lower levels of upward mobility in 2015 than 1995 in France, and propose changes in the way plants are organized as part of the reason why this may happen. I show that hollowed-out internal job ladders - or fissured workplaces - have indeed become the new organizational paradigm in France in the last two decades, and in particular in the growing non-manufacturing sectors. Motivated by these facts, I then use a matched difference-in-differences empirical design to estimate the impact of a plant's reorganization from a pyramidal to a fissured organization on workers' outcomes. I first use this framework to document changes in plants' performance in the aftermath of such reorganizations, before considering the response of workers' career outcomes to the fragmentation of their internal job ladder. The baseline result is very intuitive: the fragmentation of internal job ladders is associated with a plant's expansion, and allows firms to specialize in their most value-added generating activities. How this additional value is shared with workers is key to assessing the fissured workplace narrative. Despite finding themselves in growing workplaces, the fragmentation of a worker's internal job ladder unequivocally hinders upward mobility for those at the bottom of the hierarchy. They are however partially compensated through wage gains suggesting the existence of compensating differentials. On the other hand, retained workers at the top of the ladder do not reap shares of the increased value generated at the plant level, suggesting that reorganizations of internal job ladders also reshuffles the cards in terms of how surplus is shared. The long-lasting wage losses experienced by displaced workers are consistent with this second mechanism.

It is clear that the fragmentation of occupations at the bottom of the hierarchy obscures various margins of heterogeneity. Understanding the difference in the

task content of occupations that are fragmented towards specialized suppliers and those that are retained in plants specializing in high value-added generating activities seems crucial to better interpreting worker-level results. Empirically, the matched difference-in-differences design is perhaps too restrictive to obtain such results. Instrumental variable designs may alleviate this concern, while facing the new challenge of finding instruments capable of affecting firm and worker outcomes only through firms' organization. Potential avenues for identification could be found in making use of the introduction of specialized supplying subcontractors locally, or the roll-out of French high-speed internet as in Malgouyres, Mayer, and Mazet-Sonilhac 2019.

In that regard, instrumental variable empirical strategies such as the one suggested above would provide a narrower definition of pure "organizational shocks" faced by firms and plants, and allow for a causal estimation of the effect of reorganizations on plants' performance. In particular, it would allow us to understand whether internal job ladders are a ubiquitous part of firms' growth because they enable them to adapt to particular idiosyncratic shocks, or whether they constitute growth-inducing events in themselves.

There are few overarching theoretical frameworks available to consider the career paths of workers across firms with heterogeneous organizational structures. The closest attempts at modeling this are Kramarz, Postel-Vinay, and Robin 2014, Papageorgiou 2018 and Pastorino 2019. None of these models is able to capture the dynamic path response to a firm changing its organization towards a "fissured workplace". Building a structural framework capturing this response path could help disentangle and quantify the role of compensating differentials and changes in the rent-sharing environment faced by workers. It would also provide a general equilibrium assessment of the "fissured workplace".

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Appendices

A Data Appendix

Description of occupation codes

Table A1 describes the 2-digit classification of occupations based on the 2003 nomenclature.

Table A1: Occupation codes in the French classification

CODE	CATEGORY
10	Farmers
2	**Top managers, employees of own business**
21	Top manager / company director of handicraft firms
22	Top manager / company director of commercial firms
23	Top manager / company director of industrial or commercial firms of more than 10 employees
3	**Management positions and high-level intellectual professions**
31	Healthcare professionals, legal professionals
33	Managing position of the public administration
34	Professors and scientific professions
35	Media, art and entertainment professions
37	Administrative and commercial managers and senior staff
38	Engineers and technical managers
4	**Intermediate professions**
42	Teachers and education-related activities
43	Intermediate occupations in healthcare and social services
44	Clergy
45	Intermediate administrative occupations in the public administration
46	Intermediate administrative and commercial occupations in the private sector
47	Technicians
48	Forepersons
5	**Clerical occupations**
52	Clerical support occupations in the public administration
53	Surveillance and security occupations
54	Clerical workers
55	Commerce and retail workers
56	Individual services workers
6	**Blue collar occupations**
62	Qualified industrial blue collar workers
63	Qualified handicraft blue collar workers
64	Drivers
65	Qualified handlers, storage and transport workers
67	Unqualified industrial blue collar workers
68	Unqualified handicraft blue collar workers
69	Agricultural workers

Source: INSEE, DARES. *Nomenclature des professions et categories socioprofessionnelles des emplois salariés d'entreprise* PCS-ESE 2003.

Note: From 1982 to 2003, codes 31 and 34 were not distinguished in the two-digit classification of occupations. As a result, I merge them into occupation code 34 to remain consistent throughout the sample period.

Panel extension and smoothing the 2009 structural break

In 2009, the use of the 2-digit classification of occupations to report employees' job titles was replaced by a 4-digit classification. In addition to the job description, this new classification records the amount of responsibility given to workers, and the type of tasks attributed by the firm itself. The precision of the occupation code is much greater. This generates a structural break in the occupation series in 2009, which also appears at the 2-digit level of classification. As a result, the average rate of 2-digit occupation transitions jumps by almost 10 percentage points, and promotion and demotion rates almost double in 2009 alone.

While there is no real way to re-codify occupations from 2009 onwards into a pre-2008 classification, I can, for the purpose of my exercise, identify occupational switches and promotions or demotions that refer only to a change of job label. To do so, I use wage gains and losses, which ought to be stable over time (there is no change in the way gross earnings are reported in 2009). For each type of occupational switch I consider, I measure the average gain or loss associated with such a transition between 2006 and 2008 and between 2010 and 2012. I then measure the individual wage gain or loss experienced upon transitioning for a worker in 2009. If this wage change is outside of the 95% confidence interval for the average wage change before and after the classification change, I identify this occupational switch as "artificial" and set my switching dummy to 0. As a result, the average rate of occupation changes is smoothed out, although it is still much higher than in 2008, a feature of the time series more likely to be related to the recession in France in 2009 than to the change of classification.

The economic relevance of the internal job ladder

Table A2 reports the first step of my algorithm to construct the occupational job ladder. It reports the most frequent first full-time job titles of workers by gender and education level.

Table A2: Entry-level jobs

		Male workers	
Education level	CS2 codes	Examples	Entry wage
Below upper secondary	67, 62, 63, 64	Warehousemen, fitters	5,632
Professional training	67, 63, 62, 68	Carpenters, mechanics, janitors	8,046
University degree	67, 54, 46, 47	Unqualified administrative workers, IT staff, sales technicians	17,132
		Female workers	
Below upper secondary	54, 55, 67, 56	Unqualified administrative workers, receptionists, waitresses	3,579
Professional training	54, 55, 67, 56	Salespeople, caretakers	7,712
University degree	54, 46, 43, 55	Teachers, client advisors, secretaries	15,097

Note: This table reports the four most represented occupation code (CS2) in each gender × education level cell. I focus on workers entering the labor market for the first time between 1984 and 1994. First entry job is identified as the first full-time occupation × SIREN pair observed in the sample for workers aged between 15 and 35 years old. For each cell subsample of workers, I compute the frequency of occupation codes identified as first entry job, and report the four codes with the highest frequency. I then report the average gross yearly earning of this group of workers.

Table A3 reports a wage variance decomposition. The goal is to test whether there is a systematic component of wage variation across hierarchy layers within firms, based on my definition of a hierarchy from Section 3.2. Specifically, I decompose wage variation (i) across firms, (ii) across hierarchical layers within firms, (iii) across

occupations within layers, and (iv) within firm layers and occupations. The first line of Table A3 reports the decomposition of the total log wage variance, whereas the second line repeats the decomposition for residual wage inequality after running Mincer wage regressions of log wages on gender, age, education, experience, and tenure of workers.

Table A3: Wage variance decomposition

		Share of total variance (%)			
	Total variance	Between-firm	Within-firm across layers	Within-firm-layer across occupations	Within-occupation
		(1)	(2)	(3)	(4)
Log wages	1.48	56.05	7.39	6.56	30.15
Mincer residuals	1.05	46.28	6.93	6.80	40.11

Table A4 explores the wage gains attributed to promotions, as defined in Section 3.2. I decompose the total effect into a gain conditional on being promoted within an employing firm but across establishments of the same firm, or within a given plant. In the baseline regression model (column (2)), I control for an individual worker's local labor market (occupation code × county × industry). I find that a promotion between firms is associated with a wage gain of 40%. This effect falls to 21% for an internal promotion (within-plant). Controlling for the origin-destination firm pair (column (4)) reduces this effect to 31% (respectively 16% for a within-plant move with identical origin and destination fixed effect). Controlling for individual unobservable heterogeneity additively (column (5)), I find that an external promotion is associated with a 22% wage gain, whereas an internal promotion is associated with an exact 10% wage gain (by definition of a hierarchical layer).

Figure A1 decomposes the trend in Figure 3.1 of Section 3.2 into a within-plant and a between-firm component. The monotonic decline in average promotion rates for younger cohorts entering the labor market in the later year of my sample is

Table A4: Wage effect of a promotion

	Log gross hourly wage - (Mean = 2.54)				
	(1)	(2)	(3)	(4)	(5)
Promotion	0.336***	0.405***	0.388***	0.307***	0.224***
	(0.0120)	(0.0112)	(0.0118)	(0.0185)	(0.0153)
Within-firm between plants	-0.138***	-0.144***	-0.104***	-0.0617**	-0.0704**
	(0.0147)	(0.0153)	(0.0196)	(0.0191)	(0.0208)
Within-plant	-0.211***	-0.199***	-0.190***	-0.145***	-0.124***
	(0.0126)	(0.0125)	(0.0124)	(0.0162)	(0.0144)
Year FE	✓	✓	✓	✓	✓
Region FE		✓	✓	✓	✓
Industry FE		✓	✓	✓	✓
Occupation FE		✓	✓	✓	✓
Orig. Firm FE			✓	✓	✓
Dest. Firm FE				✓	✓
Individual FE					✓
Observations	1122949	1122755	1061929	992894	979401

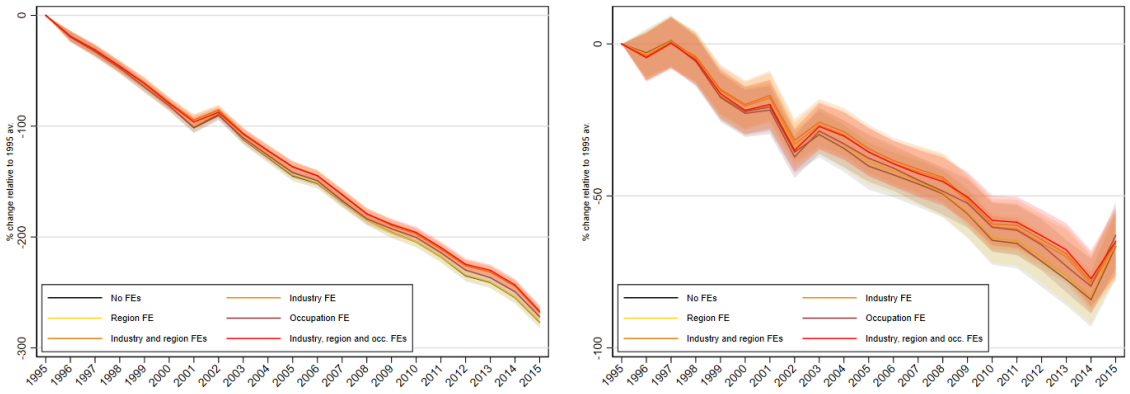
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the table reports the coefficient of a regression of current log gross hourly wage on a dummy indicating whether individual i was promoted between $t-1$ and t, a dummy indicating whether this promotion happened within firm between establishment, and a dummy taking value 1 if the promotion happened within $t-1$ plant. Individual level controls: lag log gross wage, age, age squared, LM experience, tenure at est., tenure in activity, tenure in job, tenure at est. and firm, hours, part-time status. Est. level control: size, wage bill, number of in-house activities, concentration index, share of qualified workers, multi-establishment firm dummy.

generalized. The magnitudes of the declines show that the within-plant component is a driving factor of this decline.

Figure A1 : Average promotion rate for young workers

(a) Probability of promotion within-plant (b) Probability of promotion between firms



Note: This figure reports the average promotion rate of young workers aged 15 to 30 years old by cohort. A cohort is defined as the year these workers enter the labor market for the first time in a full-time job. Each line represents the time series of estimated cohort fixed effects in an equation of the form: $y_{it} = \delta_\tau + \beta X_{it} + \gamma_{j(i,\tau)} + \gamma_{r(i,\tau)} + \delta_t + \varepsilon_{it}$ where y_{it} is worker i's probability of being promoted within-plant (Fig. A1 a) or across employers (Fig. A1 b) at time t. The coefficient of interest is δ_τ, which identifies the cohort-specific average promotion rate, with τ being the year of entry of worker i on the labor market. $\gamma_{j(i,\tau)}$ is a fixed effect for worker i's three-digit employing industry at τ, while $\gamma_{r(i,\tau)}$ is a county fixed effect that controls for the location of her first employment spell. The black line reports the raw average time series. The yellow line reports the cohort fixed effects after controlling for location of the first employment spell. The orange line controls solely for industry fixed effects, while the dark orange one control for the local labor market (industry $\times$ location). The maroon line reports the coefficients in a specification with occupation code at entry fixed effects. The red line reports the coefficients from the full specification.

B Organizational trends and composition effects

In this appendix I report the firm-level analysis of the trends discussed in Section 3.3. I then decompose aggregate time series by sectors and by plants' age.

Firm-level analysis

Table B1 reports summary statistics on the sample of firms. It is to be noted that the hierarchical structure of plants is also present at the firm level.

Table B1: Summary statistics - Firm's variables

	Mean	Std. dev.	Median	N (millions)
Employment	25.80	1172.76	5	15.7
Gross payroll (thousands of €)	1,236.696	38,500	124,202	15.9
Share of multi-est. firms	0.14	0.35	0	16.6
Number of plants	1.44	10.06	1	16.3
Number of occupations in-house	3.00	2.73	2	16.6
Number of hierarchical layers	1.68	1.11	1	16.6
Workforce concentration	0.51	0.33	0.50	16.6
Concentration across layers	0.67	0.34	0.72	16.6
Share of entry-level jobs	0.74	0.31	0.87	14.5
Share of intermediary jobs	0.15	0.24	0	14.5
Share of supervision jobs	0.08	0.18	0	14.5
Share of management jobs	0.03	0.10	0	14.5

Note: Summary statistics on the full sample of firms between 1995 and 2015.
Payroll is expressed in constant 2010 euros.

Table B2 reports the raw distribution and the employment-weighted distribution of organizational structures across firms, as discussed in Section 3.3. Most noticeable is the decline of the four-layer structures in favor of shorter internal job ladders. Contrary to the plant-level distributions, the raw distribution and the employment-weighted distribution behave quite differently. The raw distribution exhibits a large increase in fissured structures (Layer 1 only or Layer 1 and Layer 3) whereas in terms of employment, the largest increase occurs for plants with a three-layer hierarchy.

Table B2: Distribution of organizational structures - Firm level

Structure	1995	2005	2015	All	1995	2005	2015	All
Only one layer	31.19	36.94	41.15	37.33	4.50	7.17	8.55	7.25
Layer 1 + Layer 2	12.27	17.73	11.79	14.16	5.65	9.34	7.42	7.82
Layer 1 + Layer 3	3.32	4.00	7.10	4.82	1.13	1.77	3.37	2.22
Layer 2 + Layer 3	0.84	1.43	1.24	1.22	0.17	0.45	0.36	0.35
Layers 1, 2 and 3	13.19	15.33	13.64	13.82	32.26	33.98	42.22	36.64
All four layers	40.15	24.68	25.55	29.08	56.32	47.30	38.10	45.73
Pyramidal structure	95.83	94.55	91.64	93.95	98.70	97.78	96.27	97.43
Two-layer structure	16.43	23.18	20.13	20.20	6.95	11.55	11.15	10.39
Weighted	No	No	No	No	Yes	Yes	Yes	Yes
N	566,135	843,716	811,297	16,633,270	516,370	675,017	837,513	14,452,132

Note: This table reports the frequencies of several organizational structures in my sample of firms, overall and over time. Unweighted frequencies report the share of all firms in the sample with a given organizational structure. Weighted frequencies are weighted by firm's employment.

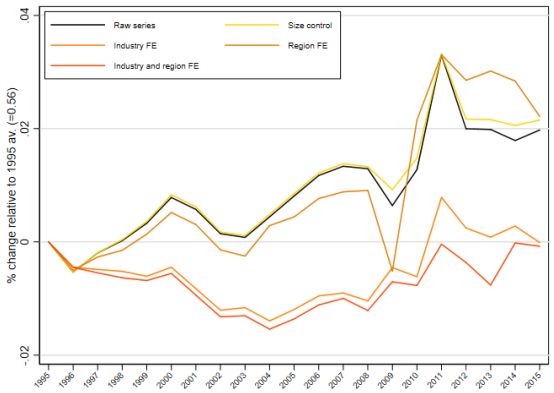
Figure B1 repeats the analysis of Figure 3.2 of Section 3.3 at the firm level. While the magnitudes of the total changes are lower than at the plant level, the qualitative patterns are similar to the plant-level series.

Figure B1: Firm-level organization of layers

(a) Number of layers



(b) Workforce HHI



Note: This figure reports the average number of hierarchical layers present in a firm's workforce (Fig. B1a) and the average Herfindahl-Hirschman index of workforce concentration across these layers (Fig. B1b) over time. Each line represents the time series of estimated year fixed effects in Equation (3.3). The black line reports the raw average time series. The yellow line reports the time fixed effects after controlling for a firm's number of employees. The sand line adds to this specification a (headquarters') *département* fixed effect. The light orange line report the coefficients in a specification with size control and the firm's main three-digit industry fixed effects. The dark orange line reports the coefficients from the full specification.

Composition effects

Figure B2 reports the times series of the average number of layers and the average Herfindahl-Hirschman concentration index at the firm level, from the following estimation regression: Each line represents the time series of estimated year fixed effects in an equation of the form:

$$y_{ut} = \delta_t + \beta Y_{ut} + \gamma_{j(u)} + \gamma_{r(u)} + \varepsilon_{ut} \tag{3.3}$$

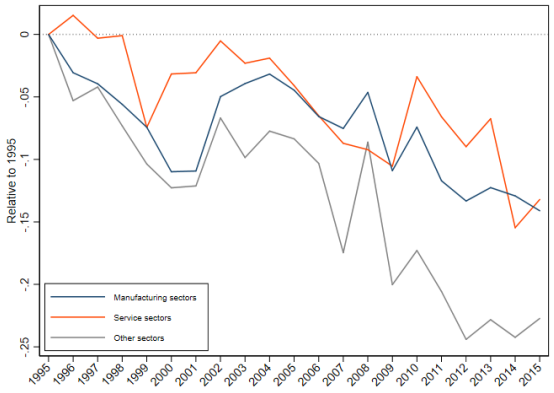
where y_{ut} is a plant u-level outcome at time t describing a plant's current organization. The coefficient of interest is δ_t, which identifies the year-specific average across units of observation. $\gamma_{j(u)}$ is a fixed effect for plant u's three-digit industry, while $\gamma_{r(u)}$ is a county fixed effect that controls for plant u's location. In this appendix, Equation (3.3) is estimated separately on a sub-sample of firms in the service sectors, manufacturing firms, and firms in the construction, transportation and commerce sectors. There is a clear divergence between manufacturing firms and the other sectors in terms of workforce concentration, akin to that observed in Figure 3.3: while the number of in-house layers uniformly decreases, concentration at the firm level decreases in manufacturing units, suggesting a diversification of the in-house IJL.

Figures B3 and B4 repeat the analysis by estimating Equation (3.3) separately on a subsample of plants or firms present in the sample throughout the period 1995 to 2015, and a sample of new entrants each year.[79] Similar to the sector-level analysis, the time series of workforce concentration across layers is the clearest in establishing the role of new entrants in driving the aggregate changes of organizational structures. Incumbent firms and plants tend to diversify their IJL, as suggested by a decline time series.

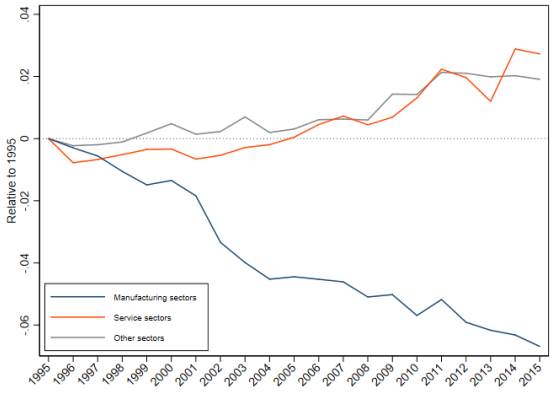
[79] In my data, the variables denoting the creation date and cessation date of a firm and/or a plant are quite noisy. I cannot therefore measure the exact age of a plant. I compromise by using a dummy variable that indicates whether the plant just entered the sample (excluding 1995), or was present before.

Figure B2: Firm-level organization of layers by sector

(a) Number of layers



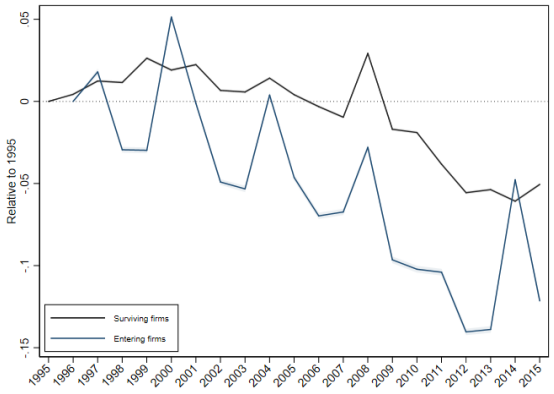
(b) Workforce HHI



Note: This figure reports the average number of hierarchical layers present in a firm's workforce (Fig. B2a) and the average Herfindahl-Hirschman index of workforce concentration across these layers (Fig. B2b) over time. Each line represents the time series of estimated year fixed effects in Equation (3.3), with the full fixed effect specification. The navy line is estimated on the manufacturing firms of my sample. The orange line is estimated on the firms belonging to the service industries. The grey line pools firms from the construction sector, the transportation sector, and the wholesale and retail trade sector.

Figure B3: Plant-level organization of layers by age

(a) Number of layers



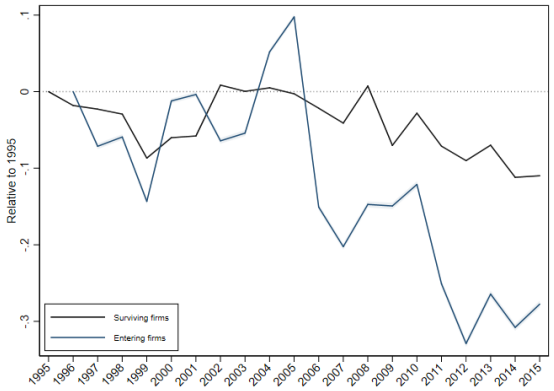
(b) Workforce HHI



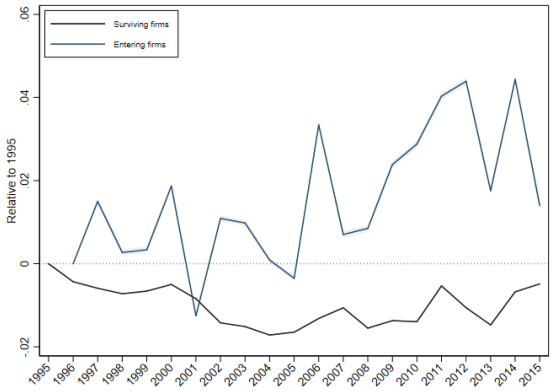
Note: This figure reports the average number of hierarchical layers present in a plant's workforce (Fig. B3a) and the average Herfindahl-Hirschman index of workforce concentration across these layers (Fig. B3b) over time. Each line represents the time series of estimated year fixed effects in Equation (3.3), with the full fixed-effect specification. The navy line is estimated on plants entering for the first time in the sample in a given year (new entrants), excluding 1995. The black line is estimated on the sample of incumbent plants between 1995 and 2015.

Figure B4: Firm-level organization of layers by age

(a) Number of layers



(b) Workforce HHI



Note: This figure reports the average number of hierarchical layers present in a firm's workforce (Fig. B4a) and the average Herfindahl-Hirschman index of workforce concentration across these layers (Fig. B4b) over time. Each line represents the time series of estimated year fixed effects in Equation (3.3), with the full fixed effect specification. The navy line is estimated on firms entering for the first time in the sample in a given year (new entrants), excluding 1995. The black line is estimated on the sample of incumbent firms between 1995 and 2015.

C Internal job ladder fragmentation events: description

In this appendix, I provide more specific details of my matching algorithm from Section 3.4.2. I then present a series of matched difference-in-differences estimations aimed at characterizing the events identified according to the definitions in Section 3.4.1.

Matching algorithm

I start with a sample of 250,310 plant $\times$ year events. According to the same definition, I identify plants that *never* fragmented an occupation during the same time period: I find 5.72 million of these. Next, I require all plants to have at least 11 employees and positive employment between years $[t-2, t+1]$. These two conditions are inherent to the definition of the fragmentation events, and therefore need to be applied to potential control units. I match plants on a number of variables aimed at capturing not only the current organizational structure of a plant, but also the trend to which they belong prior to the fragmenting event, based on the discussion in Section 3.4.2. In levels, I impose treated and control plants to belong to (i) the same decile of employment size at $t-2$, and (ii) the same quartile of $t-2$ total payroll distribution in the economy. To account for the trend prior to fragmentation events, I compute the annualized growth rate between $t-4$ and $t-2$ of (iii) the plant size by number of employees. Ideally, I would match plants according to their workforce share of each of my 25 occupation codes, or at least the trend in these employment shares. Given the restricted sample I am working with, I compromise by matching firms on (iv) the annualized growth rate of the ratio of workers in Layer 2 over workers in Layer 1. The rational for this variable comes from the nature of the worker-level treatments I consider. I focus on the fragmentation of occupations in either of these two layers, and its impact on workers in these layers or those immediately

adjacent. In order to compare workers in identical pre-event conditions, I therefore need to consider plants that are *a priori* on the same organizational trend prior to the fragmentation event. This allows me to compare plants with a similar organizational structure, if not identical IJLs. I match treated and control plants on quartiles of each of these annualized growth rates in the exact year $\tau - 2$. I then match each treated plant to a "counterfactual" establishment in the same *département* and 1-digit industry classification. This gives me a total of 31,219 treated plant matches (16,658 matches associated with the fragmentation of an occupation in Layer 2, and 14,561 associated with a fragmentation in Layer 1). I drop events occurring in 2009 from the sample of events prior to the matching, because of the changes in the classification of occupations discussed previously. The matching is quite restrictive and leads to the loss of many treated plants due to the lack of common support for some variables. At the plant level, I find a control plant in 53% of the cases.

Matching sample balancing

Table C1 (respectively C2) compares moments of targeted as well as untargeted variables in the sample of treated plants and their matched controls, when the event is a fragmentation of an occupation in Layer 2 (respectively Layer 1). In both panels, the average plant has 30 employees spread into three hierarchical layers. Between 50% and 70% of them are employed in Layer 1. In both panels, treated plants have slightly lower sales and gross value added than their matched controls. About 40% of all fragmentation events involve the fragmentation of the occupation code 46, which groups intermediary administrative and commercial jobs (such as accountants, legal clerks or advertisement assistants); around 25% of my events are associated with the fragmentation of technicians; and about 10% of events involve the fragmentation of intermediate social services occupations (which are not related to the public sector). The largest difference between the two panels is in the share of events that involve

a fragmentation of occupation code 48 (foremen, technical supervisors or site managers): I found these to be more frequent in Panel A (31%) than in Panel B (24%).[80]

Plants fragmenting an occupation from Layer 1 (Table C2) are larger but also exhibit a three-layer organizational structure, with 60% of their workforce employed in Layer 1. I find that the majority of Layer 1 fragmentation involves the suppression of unqualified production workers (codes 68 and 67, representing slightly under 35% of all events) and qualified production workers (codes 63 and 62 for another 25% of my events in both panels). This is all the more noticeable given that on aggregate, I find a strong decline in employment for occupation codes 62 and 67 in the economy, whereas all other occupation codes from Layer 1 remain relatively stable between 1995 and 2015. Amongst administrative and commercial occupations, over 12% of my fragmentation events involve the fragmentation of occupation code 54, which includes job titles such as receptionists, secretaries, or unqualified accountancy and legal services employees.

[80]Note that the total sum of frequencies exceeds 100%: this is because in some rare events, more than one occupation in the same layer (and, on even rarer occasions, the whole layer) is dropped at the same time.

Table C1: Balancing of fragmenting plants and control plants - Fragmentation of Layer 2

	Treated plants	Control plants
	(1)	(2)
Panel A: Workers from below - Layer 1		
# plants	13,494	55,802
# firms	12,179	42,856
Plant characteristics - Targeted moments		
Size (employment)	29.94	30.17
Wage bill (millions €)	1.12	1.11
Sh. entry-level occ.	0.74	0.67
Plant characteristics - Untargeted moments		
Sales (€)	4,406	6,257
Gross value added (€)	1,452	1,643
ROA	0.48	0.35
# layers	2.70	2.70
Average yearly wage (€)	39,150	37,866
Average hourly wage (€)	27.15	27.45
Event characteristics		
Occ. dropped at event (% of events)		-
48. Forepersons	31.06	-
47. Technicians	23.69	-
46. Int. admin. and commercial occ.	40.71	-
43. Int. healthcare and social serv. occ.	7.14	-
Panel B: Workers from above - Layer 3		
# plants	3,164	14,974
# firms	3,008	12,771
Plant characteristics - Targeted moments		
Size (employment)	35.67	35.99
Wage bill (millions €)	1.76	1.64
Sh. entry-level occ.	0.52	0.55
Plant characteristics - Untargeted moments		
Sales (€)	7,939	9,948
Gross value added (€)	2,716	3,599
ROA	0.47	0.28
# layers	3.01	2.90
Average yearly wage (€)	49,873	46,267
Average hourly wage (€)	33.43	31.89
Event characteristics		
Occ. dropped at event (% of events)		-
48. Forepersons	23.99	-
47. Technicians	28.73	-
46. Int. admin. and commercial occ.	39.13	-
43. Int. healthcare and social serv. occ.	11.06	-

Note: This table reports sample balancing summary statistics of establishment-level outcomes in the context of a fragmentation of Layer 2 occupations. A plant is considered to be fragmenting an occupation if the last worker in this occupation disappears from the plant's labor force at τ, and no one is re-hired in this occupation up until $\tau + 2$. The fragmented occupation must represent at least 10% of the plant's workforce between $\tau - 2$ and $\tau - 1$. The fragmenting plant's workforce excluding the fragmented occupation must not decrease by more than 10% between $\tau - 1$ and τ. Control plants are found within the same 1-digit industry code and *région*, the same size decile and the same quartile of total payroll distribution at $\tau - 2$. Treated and control plants are also matched on quartiles of annualized employment growth and quartiles of annualized growth rate of the ratio of Layer 2 over Layer 1 employment.

Table C2: Balancing of fragmenting plants and control plants - Fragmentation of Layer 1

	Treated plants	Control plants
	(1)	(2)
Panel C: Displaced workers - Layer 1		
# plants	1,107	4,462
# firms	1,036	4,005
Plant characteristics - Targeted moments		
Size (employment)	57.47	57.07
Wage bill (millions €)	2.22	2.34
Sh. entry-level occ.	0.68	0.64
Plant characteristics - Untargeted moments		
Sales (€)	9,499	12,089
Gross value added (€)	2,757	2,620
ROA	0.39	0.39
# layers	2.88	2.89
Average yearly wage (€)	39,871	40,967
Average hourly wage (€)	27.91	28.56
Event characteristics		
Occ. dropped at event (% of events)		-
68. Unqualified handicraft blue collars	14.00	-
67. Unqualified industrial blue collars	18.52	-
65. Storage and transport occ.	9.49	-
64. Drivers	8.85	-
63. Qualified handicraft blue collars	13.55	-
62. Qualified industrial workers	11.47	-
56. Individual service workers	5.24	-
55. Commerce and retail occ.	9.76	-
54. Clerical workers	12.65	-
53. Security occ.	1.99	-
Panel D: Workers from above - Layer 2		
# plants	13,454	47,915
# firms	11,544	38,560
Plant characteristics - Targeted moments		
Size (employment)	41.32	36.56
Wage bill (millions €)	1.80	1.59
Sh. entry-level occ.	0.56	0.61
Plant characteristics - Untargeted moments		
Sales (€)	7,489	8,731
Gross value added (€)	2,088	2,564
ROA	0.73	0.36
# layers	2.90	2.81
Average yearly wage (€)	45,050	45,060
Average hourly wage (€)	31.24	31.56
Event characteristics		
Occ. dropped at event (% of events)		-
68. Unqualified handicraft blue collars	14.98	-
67. Unqualified industrial blue collars	17.68	-
65. Storage and transport occ.	7.04	-
64. Drivers	6.85	-
63. Qualified handicraft blue collars	13.85	-
62. Qualified industrial workers	10.64	-
56. Individual service workers	7.02	-
55. Commerce and retail occ.	9.88	-
54. Clerical workers	12.14	-
53. Security occ.	1.98	-

Note: This table reports sample balancing summary statistics of establishment-level outcomes in the context of a fragmentation of Layer 2 occupations. A plant is considered to be fragmenting an occupation if the last worker in this occupation disappears from the plant's labor force at τ, and no one is re-hired in this occupation up until $\tau + 2$. The fragmented occupation must represent at least 10% of the place workforce between $\tau - 2$ and $\tau - 1$. The fragmenting plant's workforce excluding the fragmented occupation must not decrease by more than 10% between $\tau - 1$ and τ. Control plants are found within the same 1-digit industry code and *région*, the same size decile and the same quartile of total payroll distribution at $\tau - 2$. Treated and control plants are also matched on quartiles of annualized employment growth and quartiles of annualized growth rate of the ratio of Layer 2 over Layer 1 employment.

Table C3: Balancing of treated and control workers - Fragmentation of Layer 1

	Treated workers	Control workers
	(1)	(2)
Panel C: Displaced workers - Layer 1		
# unique ID	138	242
Worker characteristics - Targeted moments		
68. Unqualified handicraft blue collars	14.49	13.64
67. Unqualified industrial blue collars	18.12	17.77
65. Storage and transport occ.	6.52	3.72
64. Drivers	5.80	4.96
63. Qualified handicraft blue collars	7.97	10.33
62. Qualified industrial workers	13.04	11.98
56. Individual service workers	5.07	4.96
55. Commerce and retail occ.	14.49	19.83
54. Clerical workers	7.97	7.44
53. Security occ.	0.72	0.41
Age	36.82	36.07
Tenure at plant (days)	1,378	1,813
Worker characteristics - Untargeted moments		
Gender	0.66	0.67
Average yearly gross earning (€)	18,843	18,661
Average gross hourly wage (€)	14.76	13.76
Part-time status	0.20	0.19
Tenure at firm (days)	1,864	2,070
Tenure at job (plant × occ., days)	895	1,024
Panel D: Workers from above - Layer 2		
# unique ID	1,178	1,537
Worker characteristics - Targeted moments		
48. Forepersons	11.38	10.54
47. Technicians	11.46	9.69
46. Int. admin. and commercial occ.	54.58	52.57
43. Int. healthcare and social serv. occ.	22.58	21.34
Age	42.63	43.06
Tenure at plant (days)	2,566	2,500
Worker characteristics - Untargeted moments		
Gender	0.58	0.57
Average yearly gross earning (€)	34,324	36,495
Average gross hourly wage (€)	19.97	20.94
Part-time status	0.10	0.09
Tenure at firm (days)	3,084	3,114
Tenure at job (plant × occ., days)	1,507	1,554

Note: This table reports sample balancing summary statistics of worker-level outcomes in the context of a fragmentation of Layer 1 occupations. A plant is considered to be fragmenting an occupation if the last worker in this occupation disappears from the plant's labor force at τ, and no one is re-hired in this occupation up until $\tau + 2$. The fragmented occupation must represent at least 10% of the place workforce between $\tau - 2$ and $\tau - 1$. The fragmenting plant's workforce excluding the fragmented occupation must not decrease by more than 10% between $\tau - 1$ and τ. Control plants are found within the same 1-digit industry code and *région*, the same size decile and the same quartile of total payroll distribution at $\tau - 2$. Treated and control workers are identified within these matched plants pairs, with at least two years of tenure at the plant. I impose that they are employed in the same layer between $\tau - 2$ and τ, the same occupation code at time τ, and belong to the same 15-year age bin.

Table 3.6 reports summary statistics of treated and control units at the worker level in the context of a fragmentation of Layer 2 ("retained workers"). The average treated workers employed in Layer 1 when her employing plant fragments an occupation in Layer 2 (Panel A) earns about €24,000 a year, while a control worker earns an average of €23,958 yearly. Both treated and control workers are predominantly male (respectively 66% of treated workers and 64% of control workers), only 11% have a part-time contract, and both treated and control workers have been in their current job for just over 4 years (namely plant × occupation code). Because I maintain several control units per treated unit, the distribution of occupations between treated and control workers is slightly skewed. About 40% of the workers I observe are employed as qualified production workers (codes 63 and 62). The share of unqualified jobs is slightly over-represented in the group of treated workers (6.25% of unqualified production workers among the treated group (codes 54, 67 and 68). I also note that while I am matching job tenure fairly closely, treated workers systematically have more days of tenure at both the plant and the firm (the difference is almost 100 days). The sample of workers from Layer 3 (Panel B) naturally looks very different. This panel is composed of engineers and administrative and commercial senior staff in almost equal shares (respectively 48% and 50% in both treated and control groups), and is overwhelmingly male (76% of my workers). I face the same matching issues in this panel as in Panel A: despite an exact matching of treated and control workers on their job tenure (which was untargeted), I again find that treated workers have a stronger attachment to their employing firm than their control counterpart (this time the difference is 300 days). The discrepancies in earnings are also quite large, but can be partly attributed to a larger variance among these workers.

I present summary statistics of displaced workers from Layer 1 whose occupation is fragmented by their employing plant in Panel C of Table C3. The sample is very small (only 138 treated workers and 242 controls), which I attribute not to the lack

of events in the economy but to the difficulty of tracking such workers in my panel of individuals. Despite my tenure constraint, these workers have a lighter attachment to the labor force compared to the other groups of treated workers: the average job tenure is less than 3 years. I find that 33% of the identified displaced workers are employed as unqualified production workers one year prior to their displacement. Another 20% are employed as qualified production workers, and 15% as commerce and retail employees.

Main event variables

Figures C1 and C2 describe the plant-level fragmentation events in the context of a fragmentation of occupations from Layer 2 or Layer 1 respectively. Panels (a) report estimates of Equation (3.1) when the dependent variable is the number of in-house occupation codes, and Panels (b) describe estimates when the outcome is log employment of the fragmented occupation. In both instances, I verify that the number of in-house occupations drops by exactly 1 at τ.[81] In both panels (b), there is a significant pre-trend in the log employment of the subsequently fragmented occupation, suggesting that fragmented occupations are indeed "less essential" parts of the IJL (as the pre-trend is negative). Consistent with the timing of the events described in Section 3.4.1, log employment of the fragmented occupation starts dropping (even relative to the pre-trend) at $\tau - 1$. The decline at τ relative to pre-event employment and relative to non-fragmenting plants is significantly substantial, estimated at between 40% and 60%.

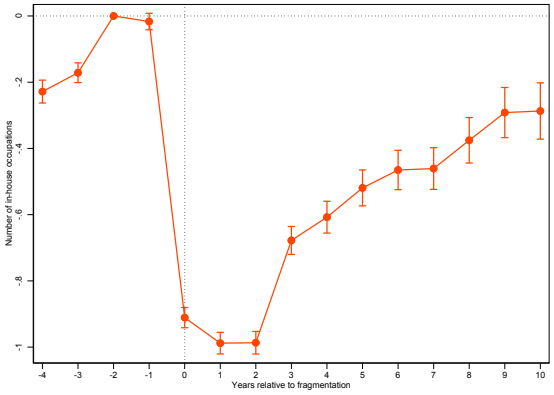
Additional employment outcomes

Figures C3 and C4 describe in further detail the dynamic response of layer-specific employment to a fragmentation of Layer 2. Figure C3 reveals that there is a strong

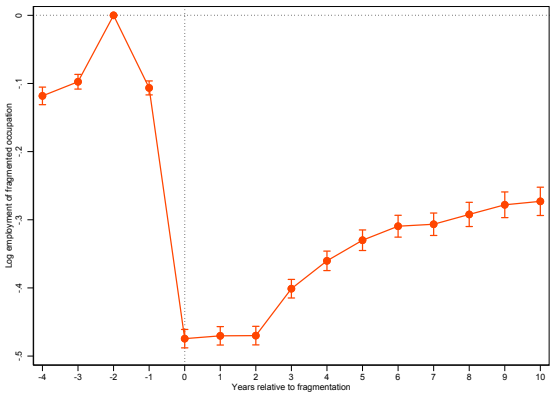
[81] Note that nothing prevents treated plants to simultaneously introduce a new occupation code in their IJL., which might lead to point estimates slightly lower than -1.

Figure C1: Fragmentation of Layer 2 occupations

(a) Number of in-house occupation codes



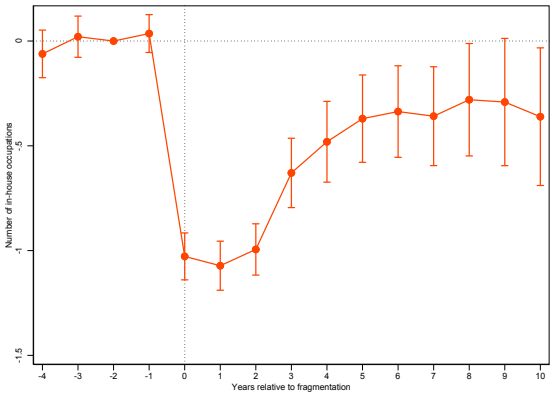
(b) Log employment of fragmented occupation



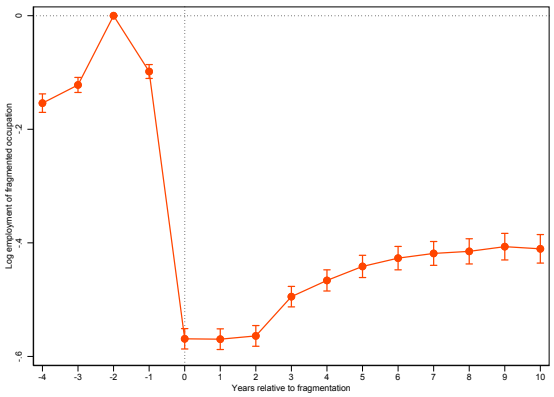
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on the number of in-house two-digit occupation codes (Fig. C1a) and on the plant's log employment of the precisely fragmented occupation (Fig. C1b), according to specification (3.1). For details of the matching procedure, see Note of Figure 3.5 of Section 3.5. 95% confidence intervals clustered at the match level are displayed.

Figure C2: Fragmentation of Layer 1 occupations

(a) Number of in-house occupation codes



(b) Log employment of fragmented occupation

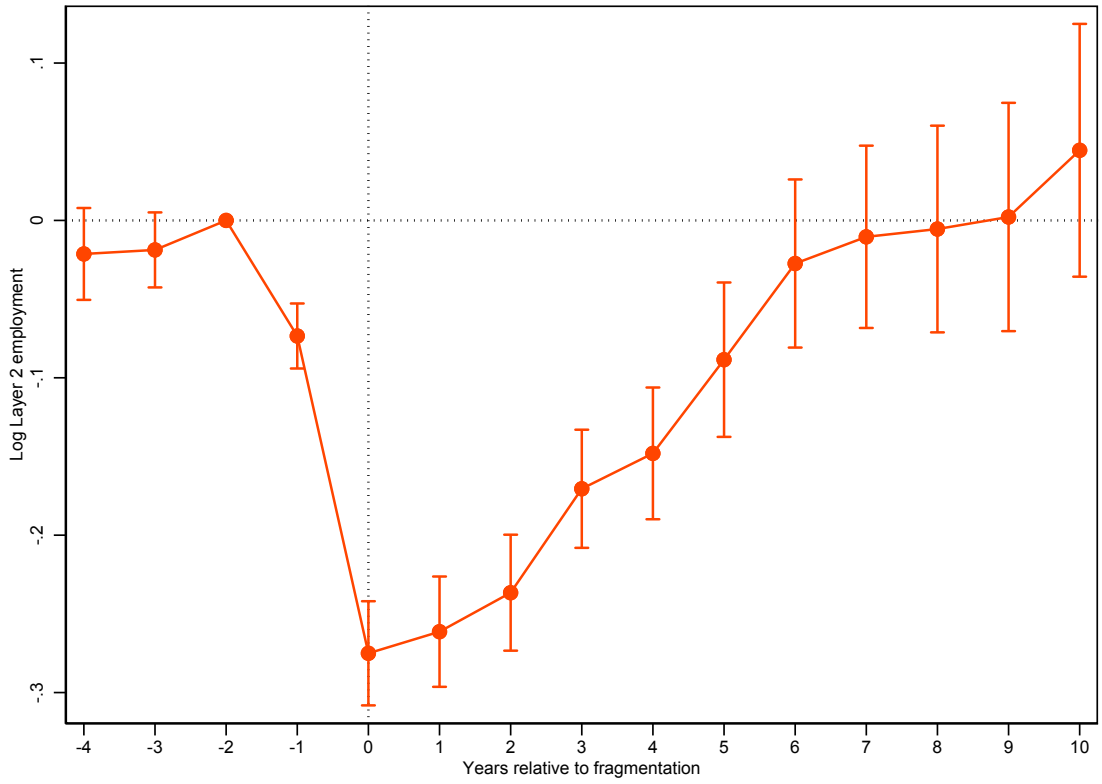


Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 1 on the number of in-house two-digit occupation codes (Fig. C2a) and on the plant's log employment of the precisely fragmented occupation (Fig. C2b), according to specification (3.1). For details of the matching procedure, see Note of Figure 3.5 of Section 3.5. 95% confidence intervals clustered at the match level are displayed.

reversion to the mean of employment for Layer 2 workers. One might worry that this reverting trend would mean that the fragmentation events identified are a tem-

porary re-composition of a plant's IJL. Figure C4 reveals that this is not the case, as employment among Layer 1 and Layer 3 occupations durably increases.

Figure C3: Plant-level Layer 2 employment



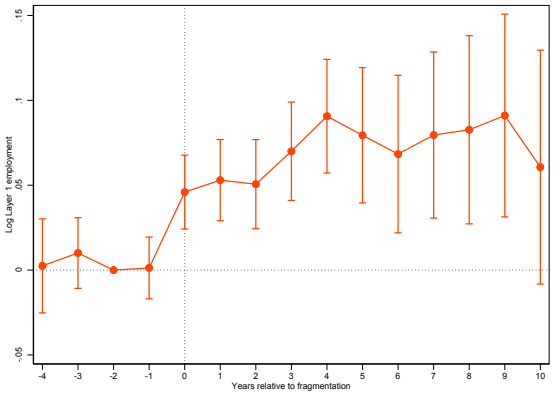
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's log employment of workers in Layer 2 (Fig. C3), according to specification (3.1). For details on the matching procedure, see Note of Figure 3.5 of Section 3.5. 95% confidence intervals clustered at the match level are displayed.

Worker-level empirical design validation

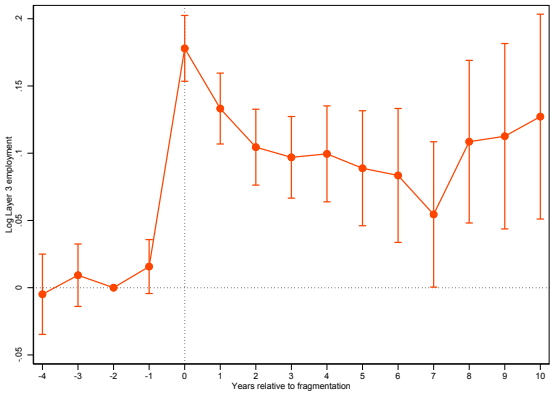
Figure C5 characterizes the fragmentation events defined in Section 3.4.1 for retained workers. I show in Section 3.4.3 that a fragmentation of a worker's own occupation is associated with a significant decline in the number of managers per worker in the new employing plants. While this may seem somehow mechanical for retained workers "from below", I show in Figure C5 that the long-lasting decline in the number of

Figure C4: Plant-level layer-specific employment

(a) Log employment of Layer 1 workers



(b) Log employment of Layer 3 workers



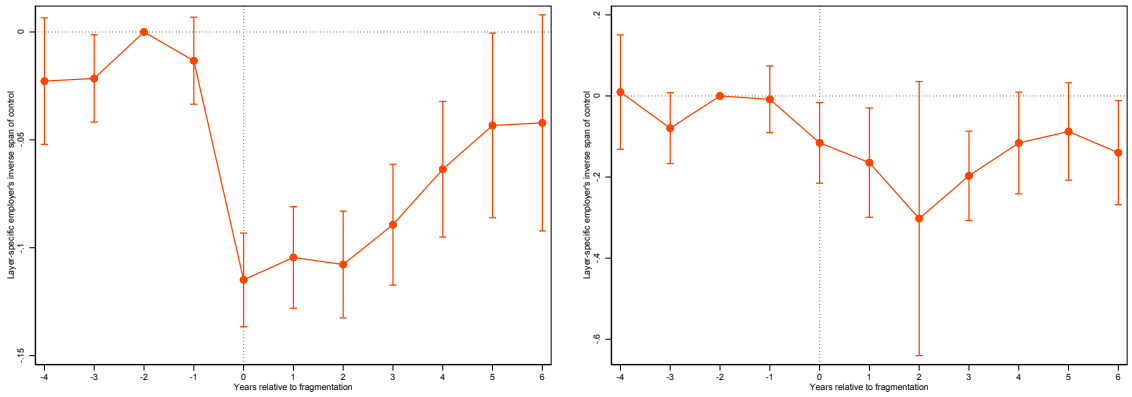
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's log employment of Layer 1 workers (Fig. C4a) and of workers in Layer 3 (Fig. C4b), according to specification (3.1). For details on the matching procedure, see Note of Figure 3.5 of Section 3.5. 95% confidence intervals clustered at the match level are displayed.

managers per worker is also relevant for retained workers "from above". This confirms that the events I identify do indeed constitute long-lasting changes in workers' IJLs.

Figure C5: Employer's inverse span of control

(a) Workers "below" (Layer 1)

(b) Workers "above" (Layer 3)



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the ratio of managers per workers employed in Layer 1 (Fig. C5a, "retained below") or in Layer 3 (Fig. C5b, "retained above"), according to specification (3.2). A retained worker "from below" is defined as a worker who is employed in occupation o of Layer 1 in plant f at time τ upon fragmentation of an occupation from Layer 2 by plant f at time τ (see Section 3.4.1). A retained worker "from above" is defined as a worker who is employed in occupation o of Layer 3 in plant f at time τ upon fragmentation of an occupation from Layer 2 by plant f at time τ (see Section 3.4.1). For each treated worker I find a counterfactual worker employed in a counterfactual plant (matched on region, industry, size, payroll and employment growth as explained in Section 3.5) in the same occupation o and in the same 15-year age-bin at time $\tau - 2$. 95% confidence interval clustered at the individual level are displayed.

D Matched difference-in-differences results

This appendix reports additional outcomes from the main analysis of Sections 3.5 and 3.6. I report the matched difference-in-differences estimated average effects over the whole post-period, as well as additional outcomes mentioned in the analysis.

Average effects

Tables D1 and D2 report average effects of the plant-level analysis in the context of a fragmentation of occupations from Layer 2.

Table D1: Average effect of fragmentation events on plants' employment

	Log Emp.	Emp. share of qualified workers	Average gross hourly wage	L1 log emp.	L2 log emp.	L3 log emp.
Post $\times$ F_{ft}	0.0449***	0.0107***	0.0001	0.0969***	-0.170***	0.0430***
	(0.0035)	(0.0014)	(0.0015)	(0.0047)	(0.0070)	(0.0066)
Mean at $\tau-2$	3.08	0.34	2.85	2.57	1.42	0.96
Adjusted R^2	0.6467	0.4695	0.8301	0.5097	0.4074	0.4975
Plant $\times$ Year	1,019,098	1,019,098	1,019,937	1,011,569	899,566	666,841

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on establishment-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.7 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of plants fragmenting an occupation in Layer 2 and the matched associated control plants. A plant is considered to be fragmenting an occupation if the last worker in this occupation disappears from the plant's labor force at τ, and no one is re-hired in this occupation up until $\tau+2$. The fragmented occupation must represent at least 10% of the place workforce between $\tau-2$ and $\tau-1$. The fragmenting plant's workforce excluding the fragmented occupation must not decrease by more than 10% between $\tau-1$ and τ. Control plants are found within the same 1-digit industry code and *région*, the same size decile and the same quartile of total payroll distribution at $\tau-2$. Treated and control plants are also matched on quartiles of annualized employment growth and quartiles of annualized growth rate of the ratio of Layer 2 over Layer 1 employment. SE. are clustered by matching groups id. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

Tables D3 - D6 report average effects of the matched difference-in-differences analysis at the worker-level, when Equation (3.2) is estimated with only pre- and post-dummies, in the context of a fragmentation of Layer 2 occupations. Table D3 reports

Table D2: Average effect of fragmentation events on plants' financial outcomes

	Log VA	Log Sales	Log unit variable costs	Log MPF	Log pay-roll
Post $\times$ F_{ut}	0.0419***	0.0450***	0.0186**	0.0196**	0.0442***
	(0.0050)	(0.0052)	(0.0077)	(0.0084)	(0.0038)
Mean at $\tau - 2$	6.610	7.852	-1.392	-2.345	13.11
Adjusted R^2	0.5528	0.5692	0.2766	0.3559	0.7529
Plant $\times$ Year	943,056	952,489	954,108	942,810	1,020,187

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on establishment-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.7 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of matched plants described in Table D1. SE. are clustered by matching groups id. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

estimates when the outcomes pertains to a worker's employing plant organizational structure and is meant to characterize more precisely the IJL changes faced by retained workers. Table D5 reports average effects estimated for occupational mobility outcomes. Table D6 reports outcomes pertaining to mobility between employing firms, and between employing plants within firms conditional on their belonging to a multi-establishment firm. Tables D4 - D8 repeat the analysis in the context of a fragmentation of occupations in Layer 1. Note that in this case, I report estimated effects for both the displaced workers and the retained workers "from above" employed in Layer 2.

Table D3: Average effect of fragmentation events on employer's organizational structure

Fragmentation of Layer 2

	# of in-house occupations	# in-house layers	Workforce HHI of concentration across layers	Inverse span of control
Panel A: Workers from "below"				
Post × $F_{f,o(\tau)}$	-0.877***	-0.150***	0.0562***	-0.0716***
	(0.0331)	(0.0114)	(0.0022)	(0.0097)
Mean at $\tau - 2$	6.864	2.968	0.650	0.332
Adjusted R^2	0.6666	0.5360	0.6907	0.4941
ID × Year	100,792	100,792	100,792	99,606
Panel B: Workers from "above"				
Post × $F_{f,o(\tau)}$	-1.220***	-0.0975***	0.0311***	-0.154***
	(0.1028)	(0.0278)	(0.0058)	(0.0567)
Mean at $\tau - 2$	7.222	3.361	0.509	0.234
Adjusted R^2	0.5284	0.4042	0.6672	0.0571
ID × Year	14,098	14,098	14,098	14,603

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure C5 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 2 at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by individual identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D4: Average effect of fragmentation events on employer's organizational structure

Fragmentation of Layer 1

	# of in-house occupations	# in-house layers	Workforce HHI of concentration across layers	Inverse span of control
Panel C: Displaced workers				
Post × $F_{f,o(\tau)}$	-0.916**	-0.483***	0.0779***	-0.161***
	(0.3608)	(0.0867)	(0.0203)	(0.0541)
Mean at $\tau - 2$	8.453	3.099	0.674	0.308
Adjusted R^2	0.4699	0.4009	0.4610	0.3995
ID × Year	3,256	3,256	3,256	3,137
Panel D: Workers from "above"				
Post × $F_{f,o(\tau)}$	-0.638***	-0.0145	0.0063*	0.0395
	(0.0693)	(0.0192)	(0.0037)	(0.0288)
Mean at $\tau - 2$	8.095	3.206	0.537	0.453
Adjusted R^2	0.6774	0.4749	0.6666	0.3864
ID × Year	25,666	25,666	25,666	25,341

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 1 occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure C5 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 1 at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by individual identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D5: Average effect of fragmentation events on worker's mobility

Fragmentation of Layer 2

	Promotion			Within-layer occ. switch		
		Within-plant	Between-firm		Within-plant	Between-firm
Panel A: Workers from "below"						
Post × $F_{f,o(\tau)}$	-0.0092***			-0.0052		
	(0.0017)			(0.0038)		
		-0.0093***	0.0005		-0.0045	-0.0009
		(0.0016)	(0.0006)		(0.0035)	(0.0012)
Mean pre-period	0.0141	0.0109	0.0021	0.0570	0.0454	0.0079
Adjusted R^2	0.0259	0.0243	0.0073	0.1162	0.1127	0.0336
ID × Year	97,229	97,229	97,229	97,229	97,229	97,229
Panel B: Workers from "above"						
Post × $F_{f,o(\tau)}$	-0.0106			-0.0001		
	(0.0073)			(0.0122)		
		-0.0120*	0.0002		-0.0037	0.0057**
		(0.0066)	(0.0023)		(0.0113)	(0.0024)
Mean pre-period	0.0257	0.0189	0.0042	0.0764	0.0669	0.0028
Adjusted R^2	0.0093	0.0057	0.0066	0.1020	0.1005	0.0057
ID × Year	14,488	14,488	14,488	14,488	14,488	14,488

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.9 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 2 at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by individual identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D6: Average effect of fragmentation events on worker's mobility

	Fragmentation of Layer 2			
	Between-firm	Within-firm between plants	Cond. on within-firm	
			Promotion	Within-layer
Panel A: Workers from "below"				
Post × $F_{f,o(\tau)}$	-0.0017	0.0084**		
	(0.0024)	(0.0041)		
			-0.0005	0.0006
			(0.0010)	(0.0012)
Mean pre-period	0.0299	0.0272	0.0014	0.0016
Adjusted R^2	0.0223	0.0242	0.0035	0.0060
ID × Year	105,259	41,614	41,397	41,397
Panel B: Workers from "above"				
Post × $F_{f,o(\tau)}$	0.0160**	0.0136		
	(0.0073)	(0.0135)		
			0.0030	-0.0015
			(0.0022)	(0.0038)
Mean pre-period	0.0381	0.0696	0.0038	0.0072
Adjusted R^2	0.0302	0.0377	0.0004	0.0103
ID × Year	15,734	7,013	7,009	7,009

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.9 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 2 at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by individual identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D7: Average effect of fragmentation events on worker's mobility

Fragmentation of Layer 1

	Promotion			Within-layer occ. switch		
		Within-plant	Between-firm		Within-plant	Between-firm
Panel C: Displaced workers						
Post × $F_{f,o(\tau)}$	-0.0012			-0.0302		
	(0.0082)			(0.0258)		
		-0.0089	0.0071		-0.0737***	0.0273***
		(0.0065)	(0.0045)		(0.0231)	(0.0099)
Mean pre-period	-0.0058	-0.0021	-0.0048	0.0948	0.0908	0.0006
Adjusted R^2	0.0242	0.0279	0.0222	0.1015	0.1059	0.0385
ID × Year	3,085	3,085	3,085	3,085	3,085	3,085
Panel D: Workers from "above"						
Post × $F_{f,o(\tau)}$	0.00124			-0.0054		
	(0.0060)			(0.0048)		
		0.0037	-0.0002		-0.0064	0.0015
		(0.0057)	(0.0018)		(0.0043)	(0.0015)
Mean pre-period	0.0489	0.0390	0.0051	0.0333	0.0272	0.0041
Adjusted R^2	0.0011	0.0010	0.0063	0.0959	0.0857	0.0444
ID × Year	24,902	24,902	24,902	24,902	24,902	24,902

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 1 occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.9 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 1 at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by individual identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D8: Average effect of fragmentation events on worker's mobility

	Fragmentation of Layer 1			
	Between-firm	Within-firm between plants	Cond. on within-firm	
			Promotion	Within-layer
Panel C: Displaced workers				
Post × $F_{f,o(\tau)}$	-0.0226	-0.0314		
	(0.0146)	(0.0202)		
			-0.0057	-0.0199*
			(0.0047)	(0.0111)
Mean pre-period	0.0491	0.0647	0.0043	0.0256
Adjusted R^2	0.0675	0.0279	0.0134	0.0192
ID × Year	3,287	2,080	2,066	2,066
Panel D: Workers from "above"				
Post × $F_{f,o(\tau)}$	-0.0078**	-0.0075		
	(0.0037)	(0.0057)		
			-0.0039*	-0.0009
			(0.0020)	(0.0011)
Mean pre-period	0.0189	0.0228	0.0034	0.0006
Adjusted R^2	0.0171	0.0341	0.0027	0.0097
ID × Year	27,334	15,456	15,361	15,361

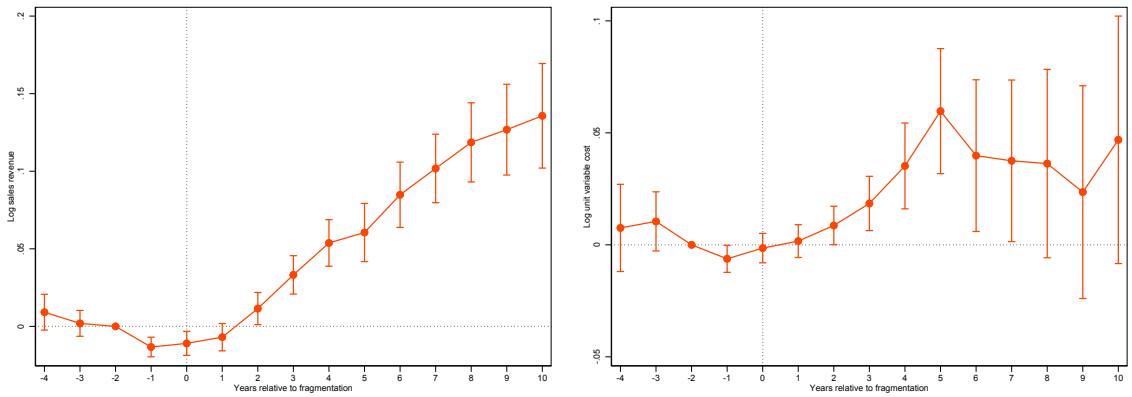
Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 1 occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.9 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 2 at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by individual identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Plant-level outcomes - Fragmentation of Layer 2 occupations

Figure D1 reports estimates of Equation (3.1) when the dependent variable is sales revenue (Fig. D1a) and unit variable cost (Fig. D1b) respectively. Unit variable costs are measured as the sum of total payroll, non-financial capital depreciation costs (amortization), and all remaining production-related expenses (purchase of material and raw material, as well as operating costs). Because these variables are only available at the firm level, the plant-level variable is constructed as the employment-weighted share of the firm-level cost.

Figure D1: Plant-level production and costs

(a) Log gross sales revenue (b) Log unit variable cost



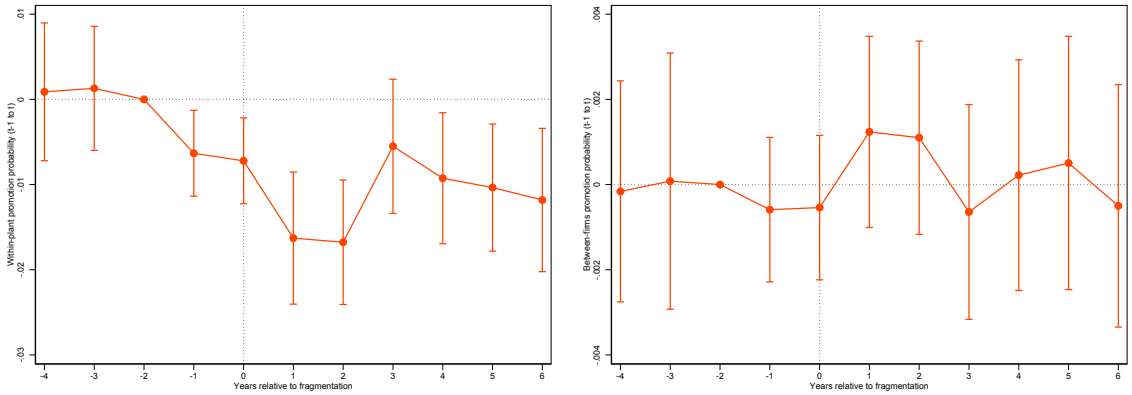
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's log gross sales revenue (Fig. D1a) and log unit variable costs (Fig. D1b) measured as the ratio of total sales over total variable cost (including labor wages and capital depreciation), according to specification (3.1). Plants' total variable costs include total wages and salaries, the depreciation of tangible and non-financial intangible assets, and purchase of intermediate inputs. For details on the matching procedure, see Note of Figure 3.5 and Appendix C. 95% confidence intervals clustered at the match level are displayed.

Retained workers in a fragmentation of Layer 2 - Additional outcomes

Figures D2 and D3 decompose the response of internal and external promotion probabilities for retained workers "from below" and "from above" in the context of a fragmentation of Layer 2 occupations.

Figure D2: Decomposing the promotion effect for workers "below"

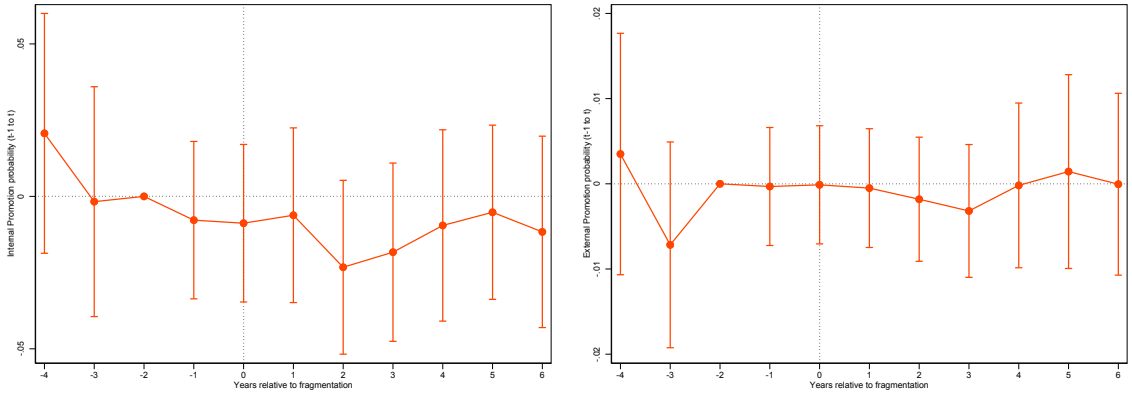
(a) Within-plant promotions (b) Between-firms promotion



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the subsequent probability of being promoted within-plant for workers employed in Layer 1 (Fig. D2a) or between-firms (Fig. D2b), according to specification (3.2). For a definition of "retained below" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure C5. 95% confidence interval clustered at the individual level are displayed.

Figure D3: Decomposing the promotion effect for workers "above"

(a) Within-plant promotions (b) Between-firms promotion



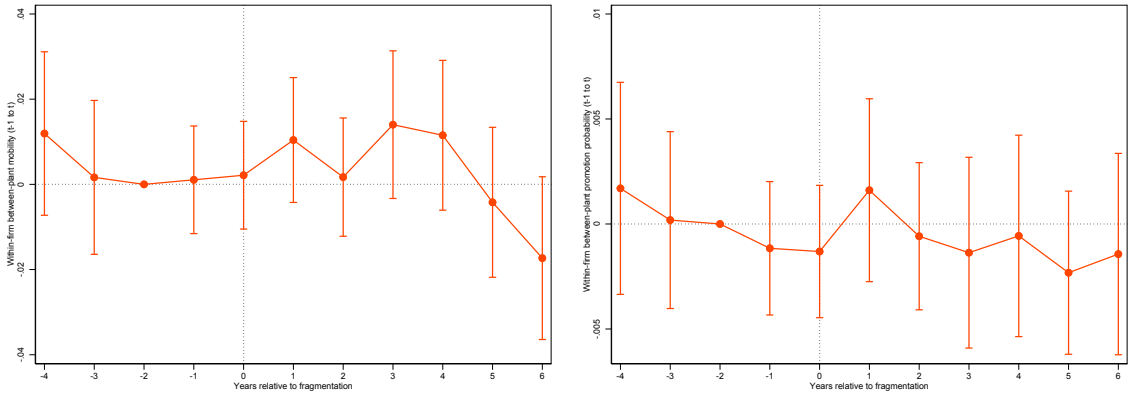
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the subsequent probability of being promoted within-plant for workers employed in Layer 3 (Fig. D3a) or between-firms (Fig. D3b), according to specification (3.2). For a definition of "retained above" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure C5. 95% confidence interval clustered at the individual level are displayed.

Figures D4 and D5 present estimates of Equation (3.2) for retained workers "from below" and "from above" in the context of a fragmentation of Layer 2 occupations, when the dependent variable is, respectively, the (conditional) probability of moving

between employing plants of the same parent firm between $t-1$ and t, and the (conditional) probability of being promoted when doing so, conditional on workers being employed in multi-establishment firms. Note that these estimates are obtained by regressing Equation (3.2) on a subsample of treated and control workers: for each sample of treated and associated control workers, I selected those workers belonging belong to a multi-establishment firm. Pre-trends between treated and control units are parallel.

Figure D4: Between-plant within-firm mobility - Workers "below"

(a) Overall mobility (b) Promotions

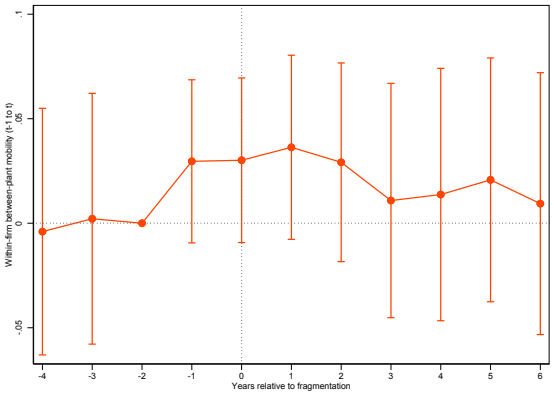


Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the subsequent probability of moving within-firm and between-plant for workers employed in Layer 1 (Fig. D4a) and of being promoted upon such a move (Fig. D4b), according to specification (3.2). For a definition of "retained below" and description of the matching algorithm, see Section 3.4 and notes to Figure C5 in Section 3.6. 95% confidence interval clustered at the individual level are displayed.

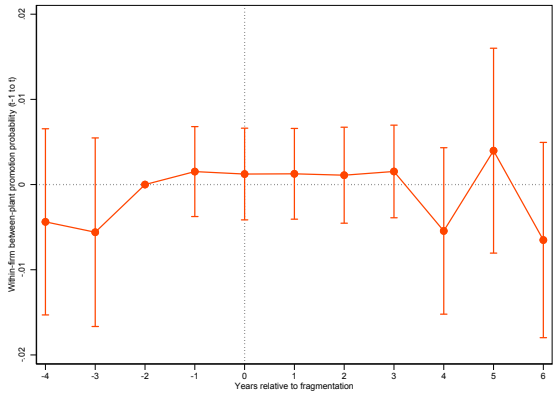
Figure D6 reports estimates of Equation (3.2) for retained workers "from below" and "from above" respectively in the context of a fragmentation of occupations of Layer 2 when the dependent variable is an individual worker's probability of changing occupation code within the current hierarchical layer between $t-1$ and t. Average effects are reported in Table D5.

Figure D5: Between-plant within-firm mobility - Workers "above"

(a) Overall mobility



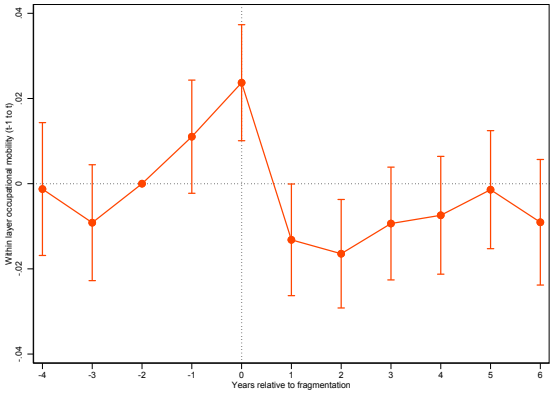
(b) Promotions



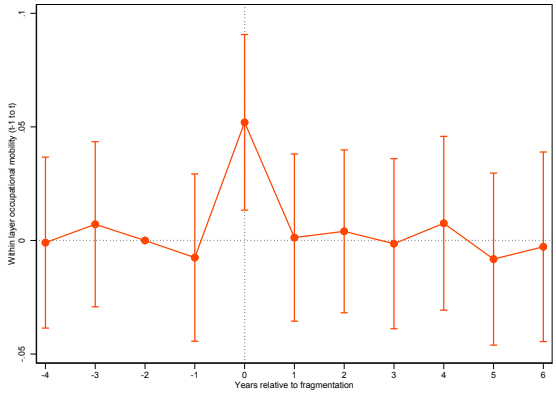
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the subsequent probability of moving within-firm and between-plant for workers employed in Layer 3 (Fig. D5a) and of being promoted upon such a move (Fig. D5b), according to specification (3.2). For a definition of "retained below" and description of the matching algorithm, see Section 3.4 and notes to Figure C5 in Section 3.6. 95% confidence interval clustered at the individual level are displayed.

Figure D6: Within-layer occupational mobility of retained workers

(a) Workers "below" (Layer 1)



(b) Workers "above" (Layer 3)

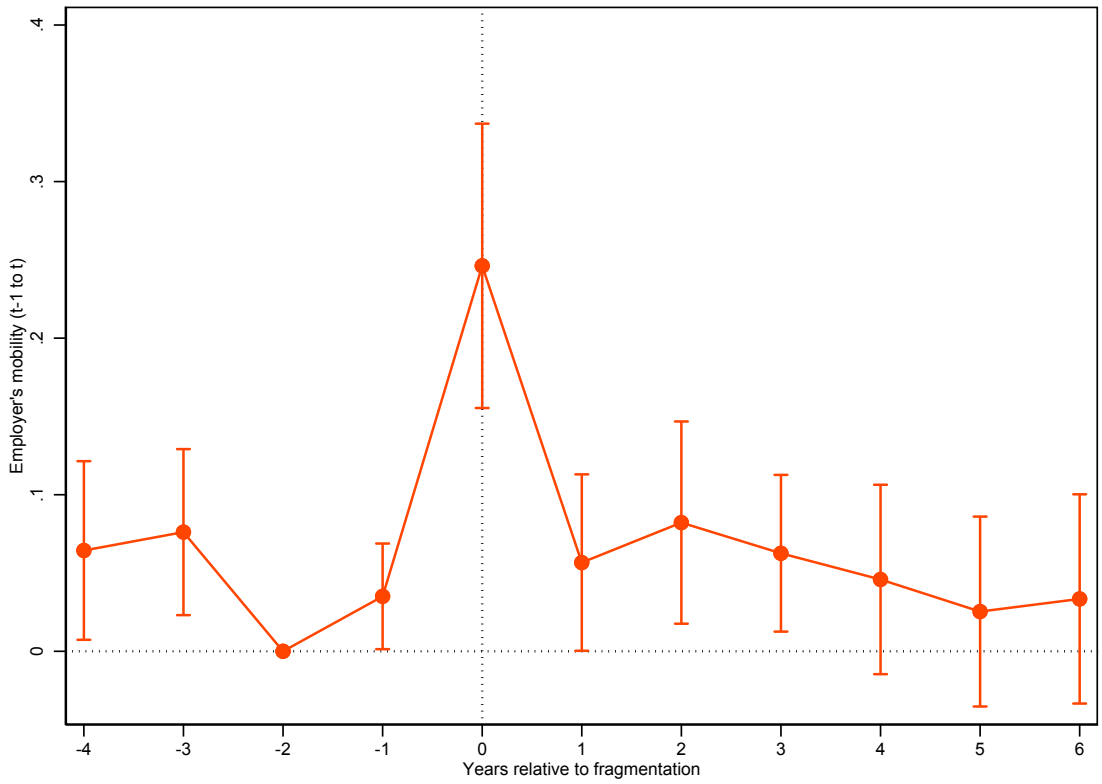


Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 2 on the yearly probability of changing 2-digit occupation code within a layer for workers employed in Layer 1 (Fig. D6a, "retained below") or in Layer 3 (Fig. D6b, "retained above"), according to specification (3.2). For a definition of the treatments and the matching algorithm see Sections 3.4.1 and 3.4.2 and notes in Figure C5. 95% confidence interval clustered at the individual level are displayed.

Displaced workers in a fragmentation of Layer 1 - Graphical outcomes

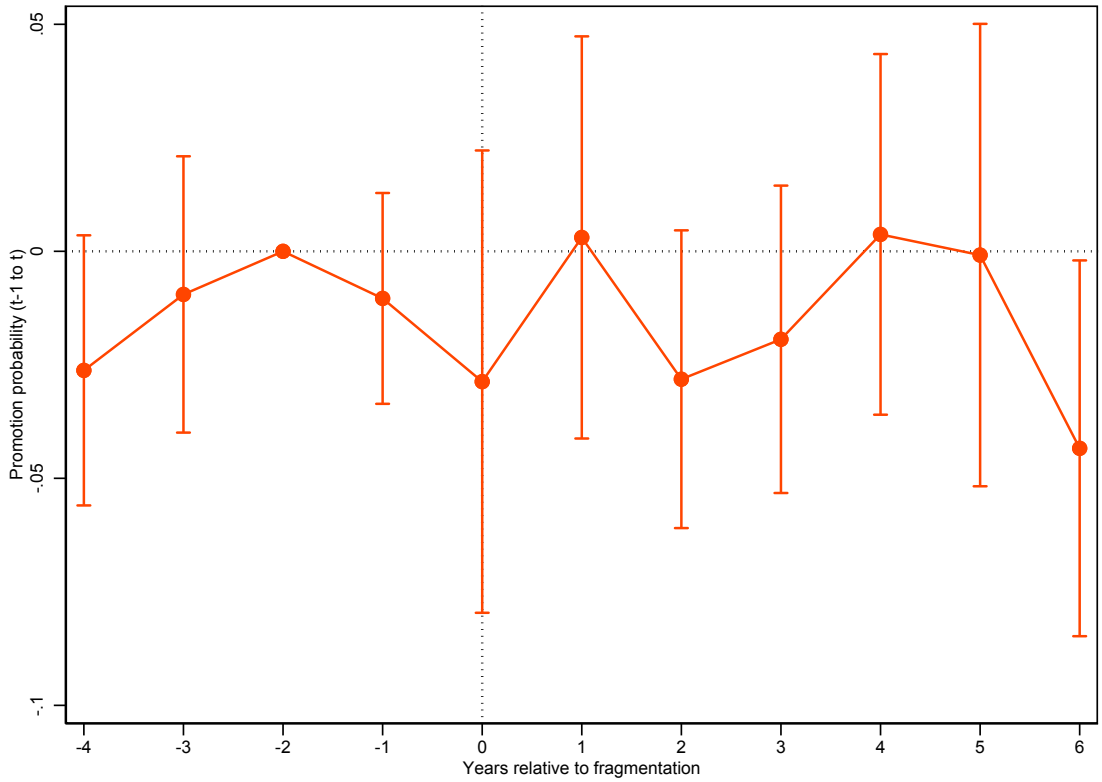
Figures D7 to D9 report the graphical outcomes mentioned in Section 3.6 for displaced workers initially employed in Layer 1. Note that in Figure D9, displaced workers who become unemployed at time τ are included. Unemployment benefits are imputed based on a 40% replacement rate for two consecutive years (see footnote 70 in Section 3.6.3).

Figure D7: Employer's mobility of displaced workers



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of a Layer 1 worker's own occupation on her probability of changing employer (firm), according to specification (3.2). A worker's inverse span of control is defined as the ratio of workers employed in the layer immediately above hers in her current employer's hierarchy, over the number of workers employed in her layer. For details on the treatment definition and the matching algorithm, see the note to Figure 3.4 and Sections 3.4.1 and 3.4.2. 95% confidence interval clustered at the individual level are displayed.

Figure D8: Promotion probability - Displaced workers

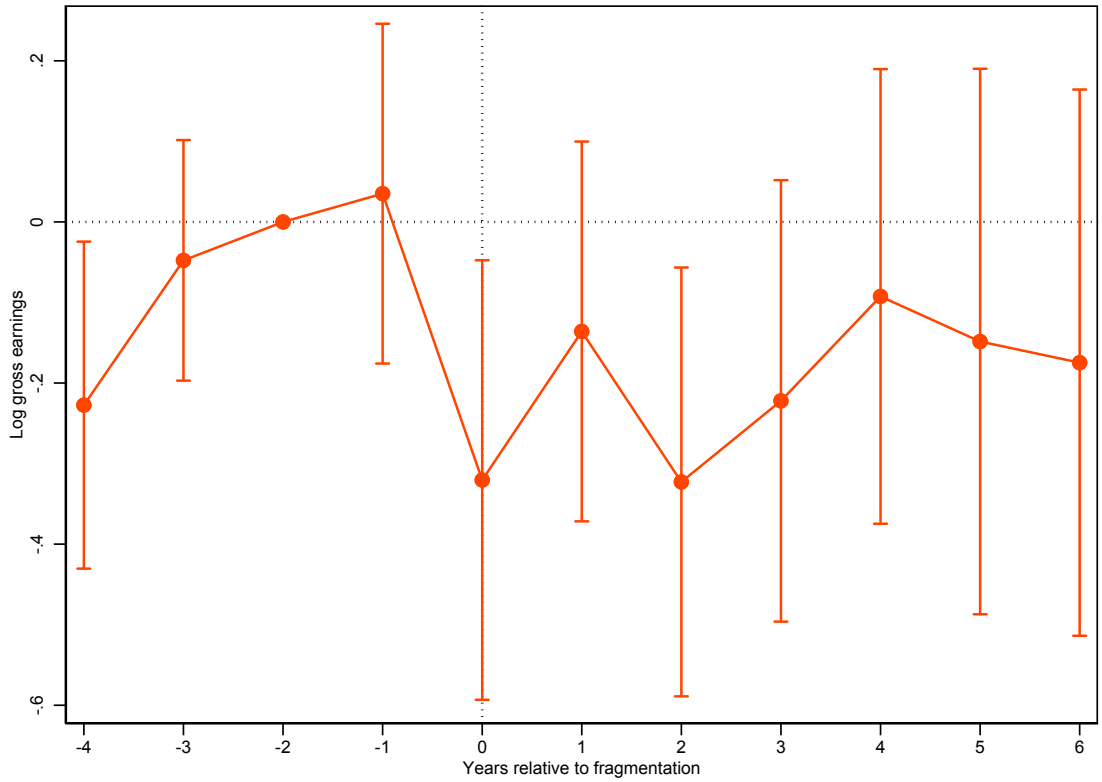


Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of a worker's own occupation in Layer 1 on her subsequent probability of being promoted, according to specification (3.2). For a definition of "displaced workers" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.4. 95% confidence interval clustered at the individual level are displayed.

Figure D10 decomposes the response of internal and external promotion probabilities for displaced workers in the context of a fragmentation of Layer 1 occupations. The discussion of these estimates can be found in Section 3.6.2.

Figure D11 reports estimates of Equation (3.2) on displaced workers from Layer 1 when their occupation is fragmented, where the dependent variable is log gross earnings. Earnings of displaced workers who do not have a valid plant identifier at time τ are set to missing. In practice, this is equivalent to estimating Equation (3.2) on displaced workers, conditional on these individuals remaining employed at time τ and subsequently. The estimates are discussed in Section 3.6.3.

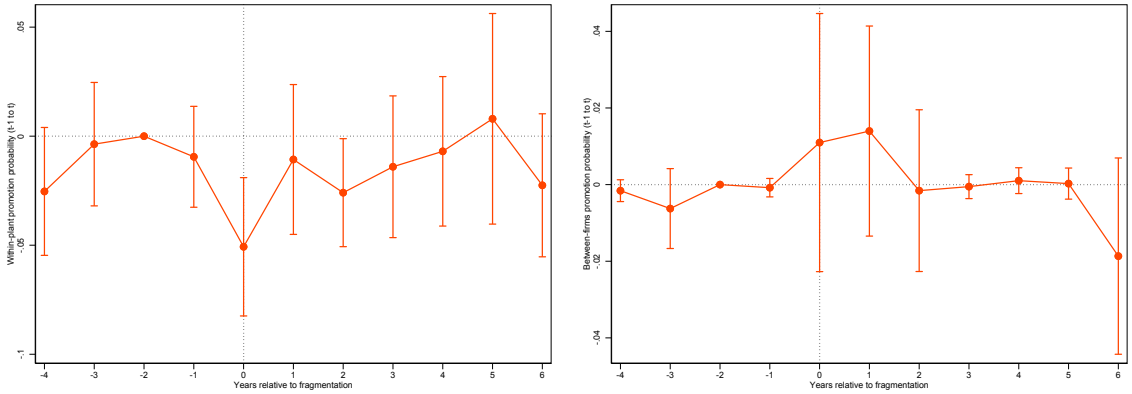
Figure D9: Log gross earnings - Displaced workers



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 1 on the log gross yearly earnings of the displaced workers conditional on these workers remaining employed upon being displaced, according to specification (3.2). For a definition of "displaced workers" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.4. 95% confidence interval clustered at the individual level are displayed.

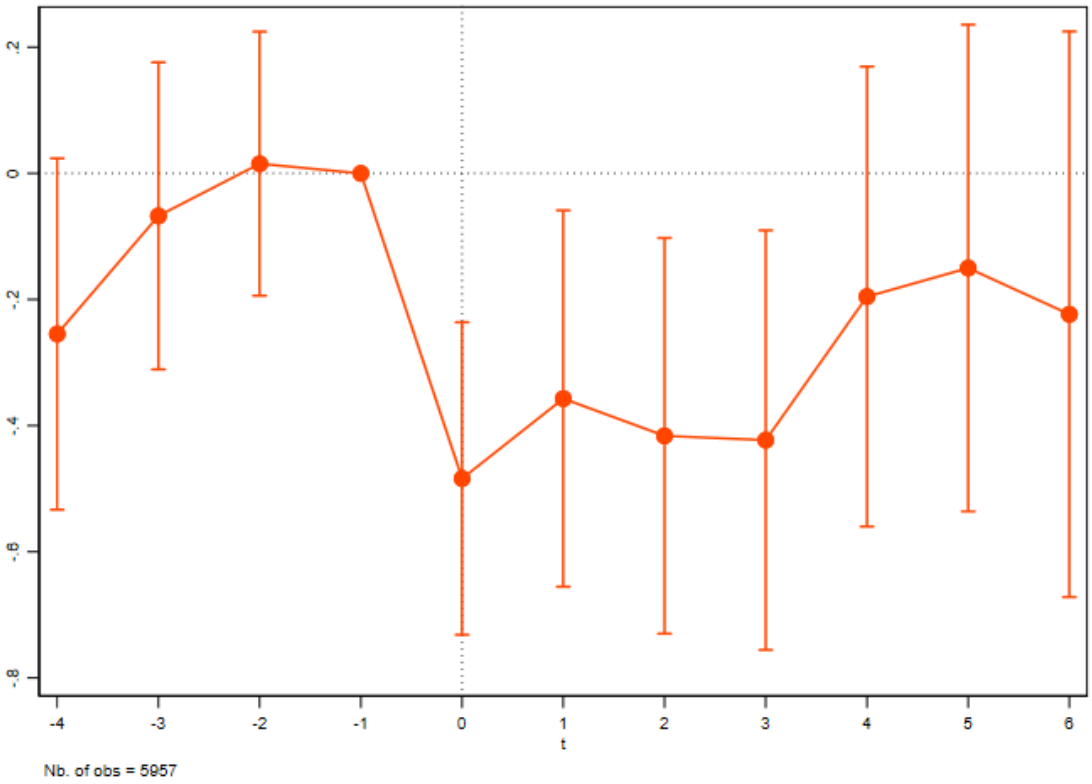
Figure D10: Decomposing the promotion effect for displaced workers

(a) Within-plant promotions (b) Between-firms promotion



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of a worker's own occupation in Layer 1 on her subsequent probability of being promoted within-plant (Fig. D10a) or between-firms (Fig. D10b), according to specification (3.2). For a definition of "displaced workers" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.4. 95% confidence interval clustered at the individual level are displayed.

Figure D11: Log gross earnings of "displaced workers" including unemployment - Fragmentation of Layer 1



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 1 on the log gross yearly earnings of the displaced workers when unemployment benefits are imputed at a 40% replacement rate, according to specification (3.2). For a definition of "displaced workers" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure 3.4. 95% confidence interval clustered at the individual level are displayed.

E Matched difference-in-differences - Robustness tests

In this appendix, I propose several estimations aimed a testing the robustness of my main results.

Plant-level outcomes robustness

Robustness to event definition - Fragmentation absent the no re-hiring constraint

One concern that can be raised about the definition of fragmentation events proposed in Section 3.4.1 is that it relies on post-event variables (namely, condition 3) imposes a no re-hiring constraint for the specific occupation code that has been fragmented for two years after the event). I argue in the main analysis that 60% of plants fulfilling conditions 1), 2) and 4) also fulfill condition 3). To verify the robustness of my results, I repeat the analysis of Sections 3.5 and 3.6 when fragmentations are only defined based on these three pre-event conditions. I report in this appendix the estimated average effects. Analysis of the full dynamic response from the matched difference-in-differences design reveals that post-fragmentation qualitative patterns are robust to this new definition. However, pre-trends are noisier, which I attribute to the added variance from including plants responding to temporary shocks.

Table E1 reveals that the estimated effects from my main analysis are robust to a slacker definition of fragmentation events. The point estimates are all of the same order of magnitudes as in the main sample, and exhibit a very clear attenuation bias towards zero.

Robustness to fragmentation type - Fragmentation of Layer 1 occupations

Table E1: Average effects - No re-hiring constraint

Fragmentation of Layer 2

	Log VA	Log Sales	Log variable costs	Log MPF	Log employment
Post $\times$ F_{ut}	0.0344***	0.0379***	0.0302***	0.0280***	0.0260***
	(0.0042)	(0.0044)	(0.0067)	(0.0072)	(0.0034)
Mean at $\tau - 2$	6.78	8.02	-1.65	-2.57	3.06
Adjusted R^2	0.6156	0.6151	0.3490	0.4179	0.6334
Plant $\times$ Year	1,076,029	1,097,125	1,086,810	1,075,710	1,133,755

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on establishment-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.5 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. SEs are clustered by matching groups id. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

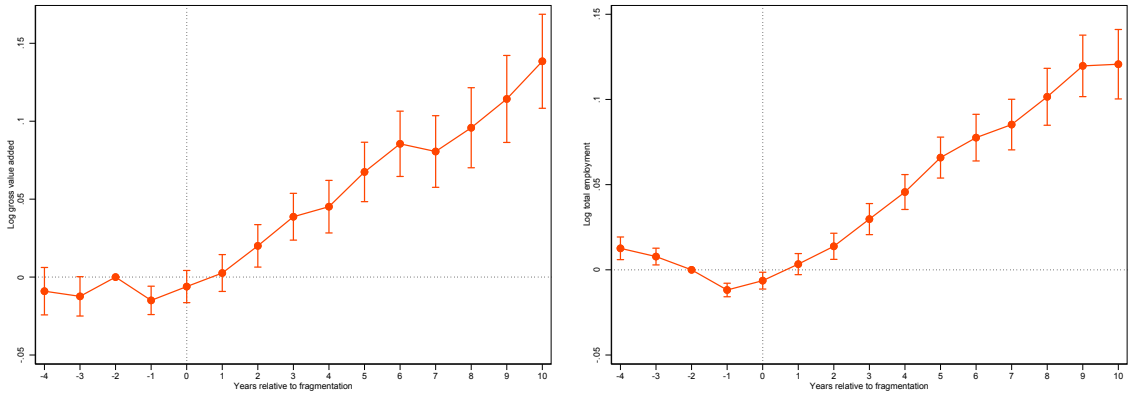
The majority of the plant-level estimates proposed in the main analysis are estimated on a sample of matched treated and control plants when the treatment involves a fragmentation of Layer 2 occupations. At the worker level however, my analysis also includes estimates for workers formerly employed in plants fragmenting entry-level occupations. Given that these types of events are the most frequent in my data, and because I need to verify that I am considering comparable plant-level events for retained and displaced workers in Section 3.6, I report in this section plant-level estimates of Equation (3.1) when the sample of analysis gathers treated and control units for a fragmentation of Layer 1 occupations. The dependent variables used are the same as that analyzed in the main analysis of Section 3.5, namely gross value added, total employment, as well as labor and multi-factor productivity measures.

Figures E1-E2 reveal that the plant-level dynamic response to an IJL fragmentation discussed in Section 3.5 is by no mean layer-specific. The qualitative patterns as well as the point estimates magnitudes are identical when considering plants fragmenting occupations from Layer 1.

Figure E1: Plant-level value-added and employment

Fragmentation of Layer 1

(a) Gross value added (b) Employment



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 1 on a plant's log gross value added evaluated at factor prices (Fig. E1a) and employment (Fig.E1b), according to specification (3.1). For each fragmenting establishment, I find a control plant by matching on three-digit industry code and region, deciles of size at $\tau - 2$, quartiles of total payroll at $\tau - 2$, and annualized growth rate of employment, and of the ratio of Layer 2 workers over Layer 1 workers between $\tau - 4$ and $\tau - 2$. 95% confidence intervals clustered at the match level are displayed.

Robustness to fragmentation type - Single-establishment firms subsample

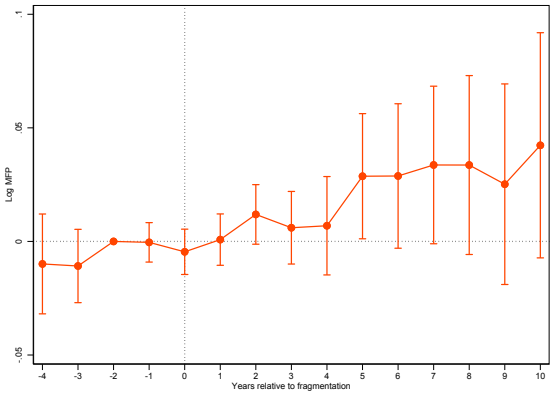
As discussed in Section 3.2.1, financial variables obtained from the FICUS database are only available at the firm level. In the main analysis of Section 3.5, I estimate the dynamic response of value added and productivity for all plants, including those belonging to multi-establishment firms. The plant-level value added or sales revenue is attributed based on the plant's share of employment in the parent firm. Because this weighting procedure is somewhat ad-hoc, I verify in this section that my results are robust to estimating Equation (3.2) on a subsample of single-establishment firms.

Figure E3 reveals that the growth-inducing effect discussed in Section 3.5.1 is robust to considering single-establishment firms and is therefore not driven by the weighting procedure.

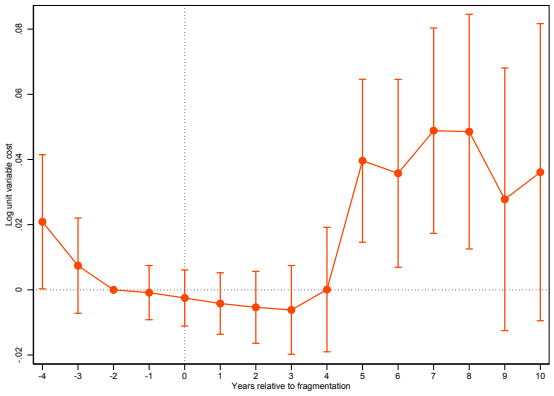
Figure E2: Plant-level productivity and costs

Fragmentation of Layer 1

(a) Multi-factor productivity



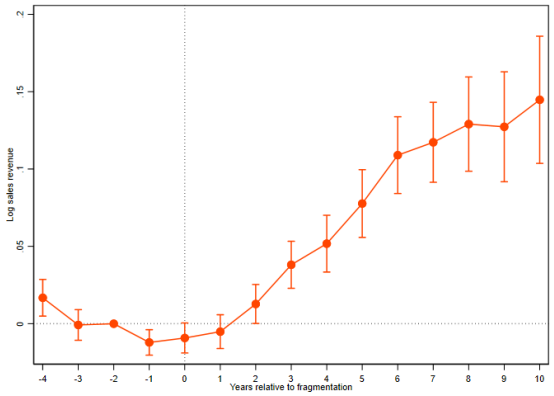
(b) Unit variable cost



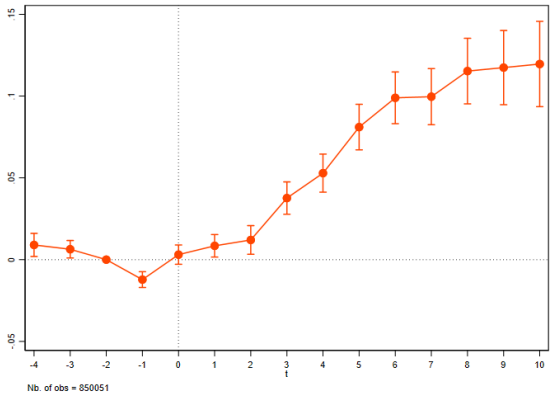
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's multi-factor productivity (Fig. E2a) and unit variable cost (Fig. E2b), according to specification (3.1). A plant's MPF is measured as the ratio of gross value added over total variable costs. Unit variable costs include intermediary inputs, labor costs and capital depreciation costs over total production sold. For details on the matching procedure, see Note of Figure E1b and Appendix C. 95% confidence intervals clustered at the match level are displayed.

Figure E3: Single-establishment firms log value added and employment

(a) Gross sales revenue



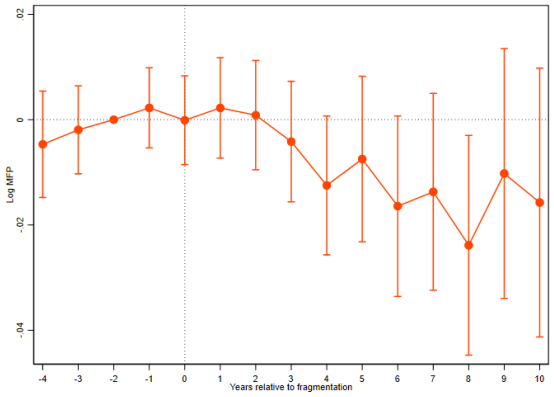
(b) Employment



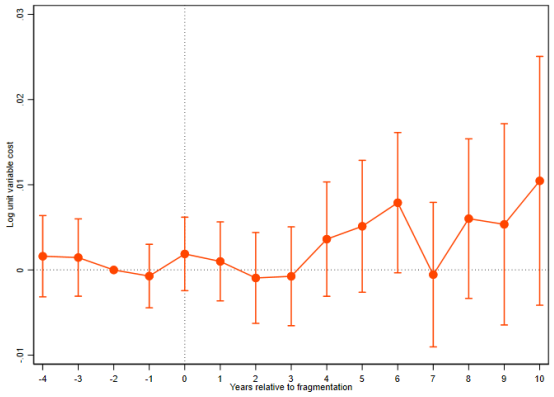
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on log gross value added evaluated at factor costs (Fig. E3a) or log employment (Fig. E3b), according to specification (3.1). The matched difference-in-differences is estimated here on a subsample of treated and control plants belonging to single-establishment firms. For details on the matching procedure, see Note of Figure 3.7 of Section 3.5. 95% confidence intervals clustered at the match level are displayed.

Figure E4: Single-establishment productivity and costs

(a) Multi-factor productivity



(b) Unit variable cost



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's multi-factor productivity (Fig. E4a) or unit variable costs (Fig. E4b), according to specification (3.1). The matched difference-in-differences is estimated here on a subsample of treated and control plants belonging to single-establishment firms. For details on the matching procedure, see Note of Figure 3.7 of Section 3.5. 95% confidence intervals clustered at the match level are displayed.

Figure E4b, however, suggests that the productivity gain established in Section 3.5.1 is in fact specific to multi-establishment firms. I do not estimate significant change in labor productivity and multi-factor productivity for single-establishment firms.

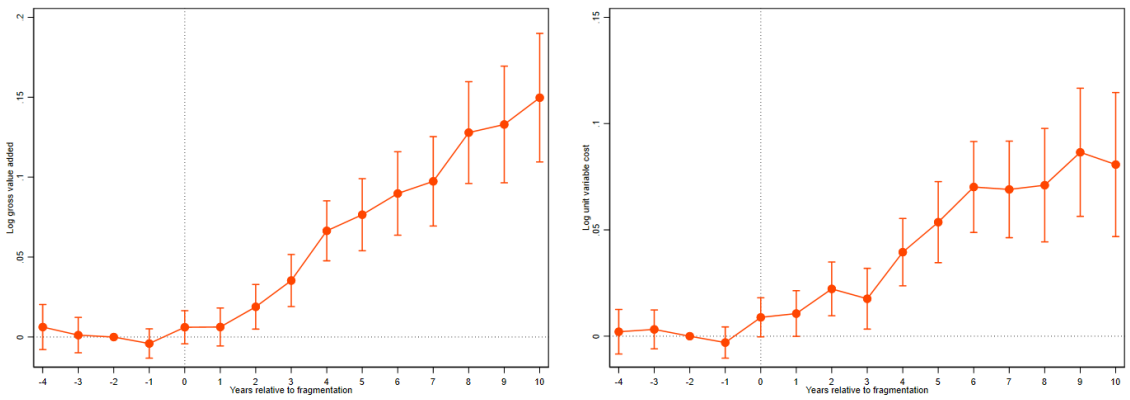
Robustness to clustering and matching

Figure E5 reports estimates of Equation 3.1 for (log) gross value added and employment, when the matching algorithm imposes a one-to-one matching (out of all the potential matches identified by the coarse exact matching, I randomly select one unique control per treated unit).

Figure E6 reports estimates of Equation 3.1 for (log) gross value added and employment, when the matching algorithm restricts coarse exact matching on level variables: (i) county, (ii) one-digit industry code, (iii) size decile and (iv) payroll quartile.

Figure E5: One-to-one matching of plants

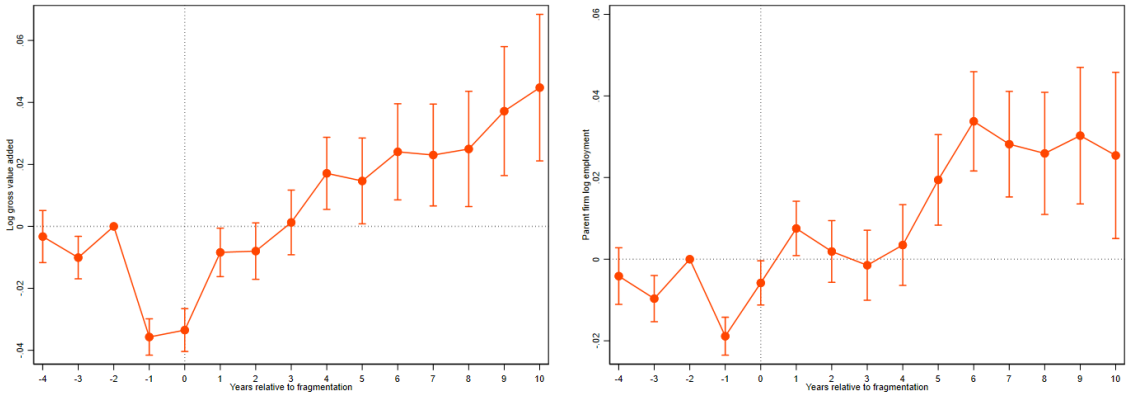
(a) Gross value added (b) Employment



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's (log) gross value added evaluated at factor costs (Fig. E5a) or (log) employment (Fig. E5b), according to specification (3.1). For details on the matching procedure, see Note of Figure 3.5 of Section 3.5. As an additional step, I randomly select one unique control unit from the pool of potential matched control plants for each treated unit. 95% confidence intervals clustered at the match level are displayed.

Figure E6: Matching of plants on level variables only

(a) Gross value added (b) Employment



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation from Layer 2 on a plant's (log) gross value added evaluated at factor costs (Fig. E6a) or (log) employment (Fig. E6b), according to specification (3.1). For each fragmenting establishment, I find a control plant by matching on three-digit industry code and region, deciles of size at $\tau - 2$, and quartiles of total payroll at $\tau - 2$. 95% confidence intervals clustered at the match level are displayed.

Table E2 repeats the analysis from Table 3.7 for different choices of standard errors clustering.

Table E2: Average effects - Clustering tests

	Log VA	Log Sales	Log unit variable costs	Log MPF	Log employment
Panel A: Baseline specification					
Post × F_{ut}	0.0419***	0.0450***	0.0186**	0.0196**	0.0449***
	(0.0050)	(0.0052)	(0.0077)	(0.0084)	(0.0035)
Panel B: Clustering at the firm-level					
Post × F_{ut}	0.0419***	0.0450***	0.0186***	0.0196**	0.0449***
	(0.0049)	(0.0052)	(0.0070)	(0.0077)	(0.0035)
Panel C: Clustering at the county × industry					
Post × F_{ut}	0.0403***	0.0417***	0.0228	0.0230	0.0447***
	(0.0084)	(0.0080)	(0.0184)	(0.0198)	(0.0047)
Mean at $\tau - 2$	6.610	7.852	-1.392	-2.345	3.08
Adjusted R^2	0.5528	0.5692	0.2766	0.3559	0.6467
Plant × Year	943,056	952,489	954,108	942,810	1,019,098

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 occupations on establishment-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.5 and average the ten post-event coefficients to estimate the aggregate effect reported in this table. SEs are clustered by matching groups id in Panel A, by plant id in Panel B, and two-way clustered by county and (three-digit) industry code in Panel C. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

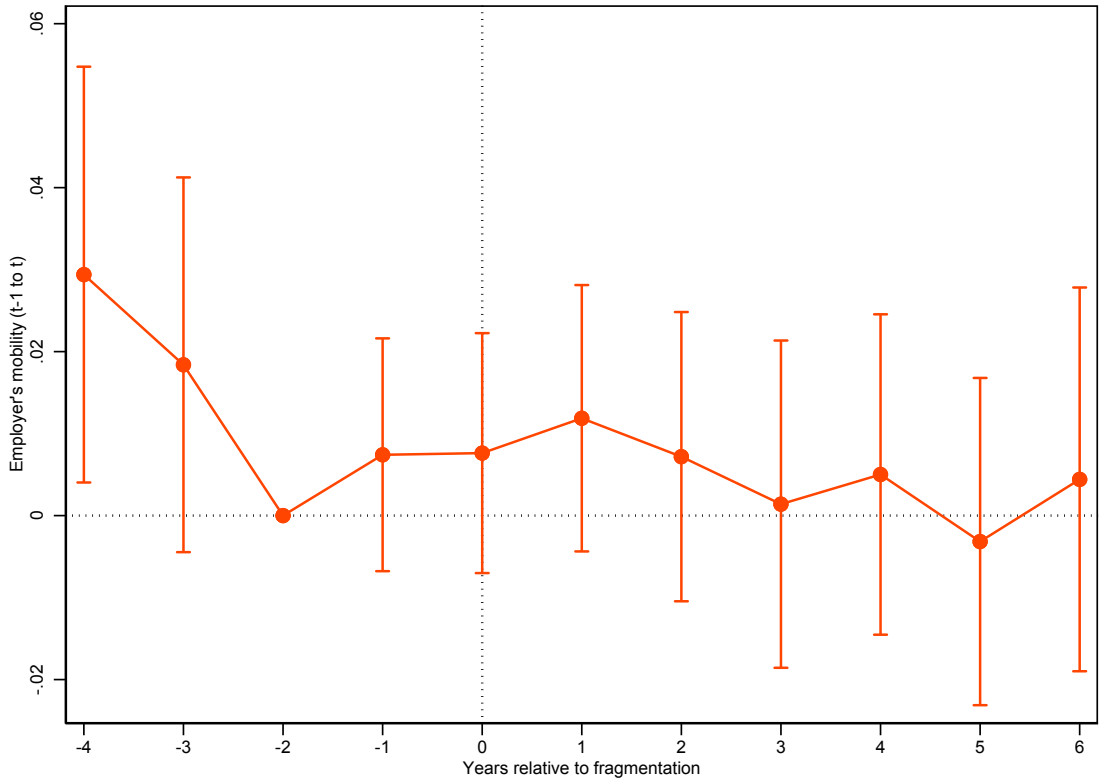
Worker-level outcomes robustness

Retained workers "from above" in a fragmentation of Layer 1 - Robustness

In this section, I propose a simple robustness test for my empirical estimates on retained workers "from above". By constructing the displaced worker group, I identify plants' fragmenting occupations from Layer 1. Whereas I focused my analysis on displaced workers, here I propose estimates of worker-level outcomes when considering retained workers employed in Layer 2 in plants' fragmenting occupations from Layer 1. Because I showed in Appendix E that a fragmentation of Layer 1 occupations has an identical effect at the plant level as a fragmentation of Layer 2 occupations,

I can compare responses of worker-level outcomes for retained workers "from above" in both cases.

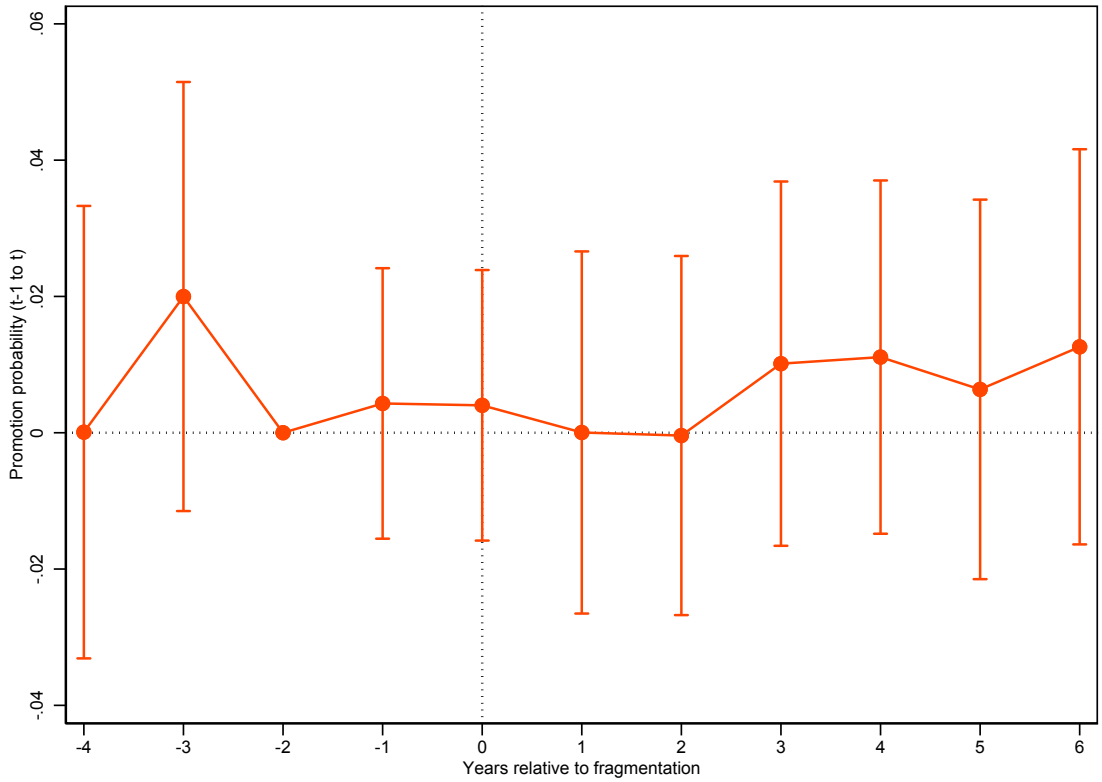
Figure E7: Employer mobility for "retained above" - Fragmentation of Layer 1



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 1 on the subsequent probability of changing employer (firm) for workers employed in Layer 2, according to specification (3.2). A "stayer from above" is defined as a worker who is employed in occupation o of Layer 2 in plant f at time τ upon fragmentation of an occupation from Layer 1 by plant f at time τ. For each treated worker I find a counterfactual worker employed in a counterfactual plant (matched on region, industry, size, payroll and employment growth as explained in Appendix C) in the same occupation o and in the same 15-year age-bin at time $\tau - 2$. 95% confidence interval clustered at the individual level are displayed.

All qualitative patterns are confirmed for retained workers "from above". Figure E10 is the only estimation that suggests a null effect on the earnings of retained workers "from above". However, the magnitude of the coefficients (although insignificant) are similar to those estimated for retained workers employed in Layer 3.

Figure E8: Promotion probability for "retained above" - Fragmentation of Layer 1



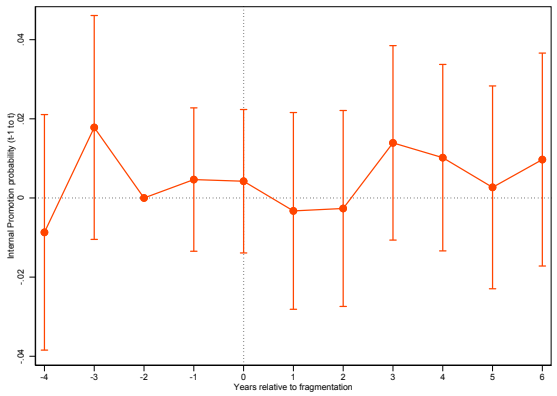
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 1 on workers employed in Layer 2's subsequent probability of being promoted, according to specification (3.2). For a definition of "retained above" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure E7. 95% confidence interval clustered at the individual level are displayed.

Robustness to clustering

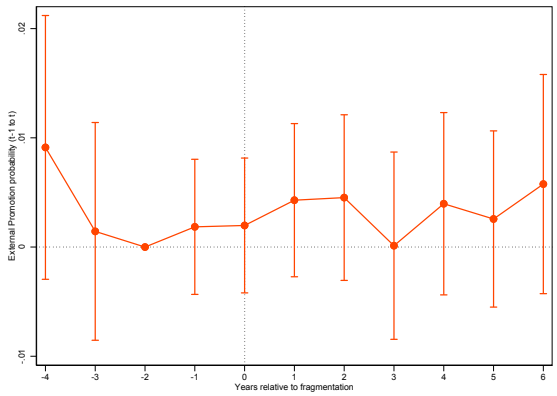
Finally, Table E3 repeats the analysis of Table 3.8 when standard errors are clustered at the match level rather than the worker level.

Figure E9: Decomposing the promotion effect for Layer 2 workers

(a) Within-plant promotions



(b) Between-firms promotion



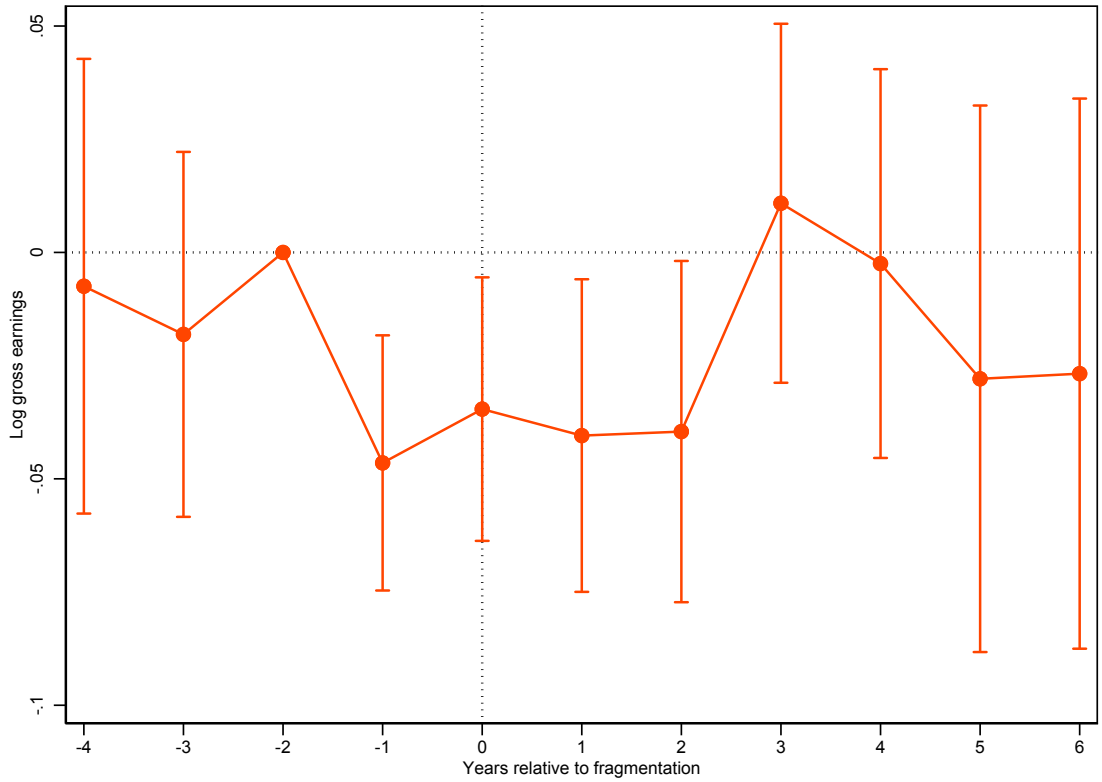
Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 1 on the subsequent probability of being promoted within-plant (Fig. E9a) or between-firms (Fig. E9b) for workers employed in Layer 2, according to specification (3.2). For a definition of "retained above" and description of the matching algorithm, see Section 3.4 and notes to Figure E7. 95% confidence interval clustered at the individual level are displayed.

Table E3: Average effect of fragmentation events on worker's outcomes

	Employer mobility	Promotion	Within-layer occ. switch	Log gross earnings
Panel A: Workers from "below"				
Post × $F_{f,o(\tau)}$	-0.0017	-0.0092***	-0.0046	0.0213***
	(0.0025)	(0.0016)	(0.0038)	(0.0083)
Mean pre-period	0.0358	0.0127	0.0399	9.96
Adjusted R^2	0.0160	0.0172	0.0595	0.2232
ID × Year	97,618	97,233	97,233	101,075
Panel B: Workers from "above"				
Post × $F_{f,o(\tau)}$	0.0150**	-0.0101	0.0090	-0.0178
	(0.0030)	(0.0070)	(0.0109)	(0.0211)
Mean pre-period	0.0510	0.0334	0.06493	11.03
Adjusted R^2	0.0233	0.0139	0.0339	0.2279
ID × Year	14,535	14,488	14,488	14,930
Panel C: Displaced workers				
Post × $F_{f,o(\tau)}$	0.0495***	-0.0052	-0.0330	-0.143
	(0.0133)	(0.0078)	(0.0253)	(0.0916)
Mean pre-period	0.0171	-0.0044	0.0858	9.37
Adjusted R^2	0.0467	0.0380	0.1155	0.3757
ID × Year	3,110	3,085	3,085	3,316

Note: This table reports difference-in-differences estimates of the effect of a fragmentation of Layer 2 (respectively 1 in Panel C) occupations on worker-level outcomes. I estimate a flexible specification that allows for dynamic treatment effects as depicted in Figure 3.9 and average the six post-event coefficients to estimate the aggregate effect reported in this table. The regressions are estimated on the sample of workers employed by a plant fragmenting an occupation in Layer 2 (respectively 1 in Panel C) at the time of the event and the matched associated control workers. Control workers are found within the same 2-digit occupation code and 15-year age bin within a control plant associated with the treated employing plant. SE. are clustered by matching group identifier. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure E10: Log gross earnings of "retained above" - Fragmentation of Layer 1



Note: This figure displays matched difference-in-differences estimates of the effect of a fragmentation of an occupation in Layer 1 on the log gross yearly earnings of workers employed in Layer 2, according to specification (3.2). For a definition of "retained above" and description of the matching algorithm, see Sections 3.4.1 and 3.4.2 and notes to Figure E7. 95% confidence interval clustered at the individual level are displayed.