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Essays on Productivity Growth: Spinouts, Noncompetes, and Inequality

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ESSAYS ON PRODUCTIVITY GROWTH:
SPINOUTS, NONCOMPETES, AND INEQUALITY

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A DISSERTATION
PRESENTED TO THE FACULTY
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Abstract

This dissertation consists of three essays on productivity growth. The first chapter empirically studies within-industry employee spinout (WSO) formation in the United States. I begin by constructing a dataset which matches venture capital (VC) funded startups to the previous employers of their founders. First, I find evidence that, per founder, WSOs have higher revenue and valuation, and more employees, than non-WSOs. They are also less likely to fail and more likely to be acquired or IPO. Second, I find a statistically significant relationship between corporate R&D and subsequent WSO formation. The relationship can account for close to one tenth of VC-funded startup employment during the sample period.

The second chapter is a quantitative analysis of the effect of noncompete agreements (NCAs) on aggregate productivity growth. Motivated by the first chapter, I develop a general equilibrium model extending a quality ladders model of endogenous growth to include R&D-induced WSOs and NCAs. I quantify the model using aggregate data as well as the results of the first chapter. I then explore several policy counterfactuals. The main result is that a reduction of all barriers to the use of NCAs increases the annual growth rate by 0.21 percentage points and welfare by 3.24% in consumption-equivalent terms. I also find that R&D subsidies can reduce growth and welfare by worsening the allocation of R&D.

The third chapter, coauthored with Eduardo Fernández-Arias, examines the per capita output growth performance since 1960 of countries in Latin America and the Caribbean (LAC). Using a worldwide panel of countries, we first find strong evidence that, relative to countries with the same output per capita, LAC countries have a

large average per capita growth shortfall (of 0.7% per annum) that is almost entirely driven by subpar productivity growth. Even since 1990, regional productivity growth is subpar, though less so. Second, we find that the high Gini index of disposable income in LAC countries can account for most of the productivity growth shortfall. However, it is also associated with a high rate of factor accumulation and, therefore, cannot account for the region's poor per capita output growth.

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To my parents and sister.

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Chapter 1

Corporate R&D and Within-Industry Spinout Formation

1.1 Introduction

The entry of new firms contributes significantly to innovation and productivity growth. Many innovative startups employ knowledge that their founders and employees gained while working at firms in the same industry. Such firms are known in the literature as within-industry spinouts (WSOs or spinouts), and there are many well-known examples. The most commonly cited example is the many spinouts of Fairchild Semiconductor, which include Intel and AMD. Fairchild itself is a spinout of Shockley Laboratories, another semiconductor firm. Moreover, former AMD employees founded NVIDIA, which competes with both Intel and AMD. Another example in semiconductors is Qualcomm, the leading designer and manufacturer

of networking chips, which was founded by former employees of Linkabit, another leading company in digital communications.

More broadly, successful within-industry spinouts can be found in many industries and time periods. In the software industry, Adobe was founded by former employees of the Xerox PARC research laboratory. The teleconferencing application Zoom was founded by a former vice president of engineering at Cisco Webex. Salesforce, a customer relationships management software company, was founded by a former executive of Oracle, one of its main competitors. In the pharmaceutical sector, Vertex Pharmaceuticals, which specializes in rational drug design, was founded by a scientist previously employed at Merck in the same capacity.¹ The steel manufacturer Steel Dynamics – the third largest in the United States – was founded by former executives of Nucor, the largest steel producer.² Examples can also be found outside of the high technology and manufacturing sectors. The management and business consulting firm Bain & Company was founded by a former vice president of Boston Consulting Group. In the financial sector, Bloomberg was founded by a former partner at Salomon Brothers who had set up internal computer systems.

In all of the above cases, the WSO founders used knowledge that they acquired at their previous employer when founding their startups. The question motivating this chapter is whether R&D spending at the original firm plays a role in the generation and transfer of this knowledge, thereby inducing within-industry spinout formation.

¹Vertex founder Joshua Boger's goals for the company were to "become Merck, but better; design better drugs, faster; and become the 21st century biopharmaceutical company." (see Werth 2014)

²Other well-known examples in manufacturing can be found in the hard disk drive industry (Franco and Filson 2006), the laser industry (Klepper and Sleeper 2005), and the early automotive industry (Klepper 2007).

This has important implications for understanding the impact of corporate R&D on innovation and productivity growth, as within-industry spinouts may constitute another socially valuable output of R&D spending. And it has implications for the effect of within-industry spinout formation on aggregate productivity growth, as competition by spinouts may be a privately costly output of R&D, disincentivizing innovation by incumbent firms.³

To be precise, in this chapter I test whether a firm’s R&D spending is associated with subsequent WSO formation by its employees. The hypothesis motivating this specification is that executives, R&D managers, and R&D employees learn-by-doing how to innovate in their field. Due to contracting frictions and strategic disagreements, which have been highlighted in the literature (see below), this additional know-how sometimes ends up deployed in a new firm rather than within the parent firm. As a result, R&D spending leads to a higher likelihood that a firm’s employees form competing within-industry spinouts.

I begin by constructing a dataset that matches parent firms to their spinouts. The dataset combines Compustat data on publicly traded firms and private Venture Source data on venture capital-funded startups and their founders. Venture Source is the only dataset on startups with data on the previous employers of founders, executives and board members. As there are no common company identifiers, I use string matching techniques (e.g., regular expressions) to match Venture Source biographical data to Compustat firm name data. I define a startup as a within-industry spinout if its CEO, CTO, President, Chairman or Founder joined the startup in its first three

³I study these questions in Chapter 2.

years after being most recently employed at a firm in Compustat in the same 4-digit NAICS industry. Using this approach I match 2,475 founders of WSOs to their parent firms. Finally, I match this dataset to the NBER-USPTO database, which contains information on all US patents.

I have two sets of results. First, I compare WSOs to ordinary startups. I document that, on a per founder basis, WSOs tend to be significantly larger in terms of employment, revenue, and valuation. They are also more likely to IPO and less likely to go out of business. The differences are quite substantial: WSOs are about 40% larger and 0.5 (2.0) percentage points less (more) likely to go out of business (be acquired or IPO) in any given year. These results are consistent with findings in Babina and Howell 2019, Gompers et al. 2005, Baslandze 2019, and others in the spinouts literature.

For my main result, I examine the relationship between R&D spending and spinout formation. I find a statistically significant relationship between R&D spending at the firm level and subsequent within-industry spinout formation. The relationship holds when controlling for relevant firm-level controls and using firm, firm age, industry-year and state-year fixed effects. It is also economically significant, accounting for nearly one tenth of employment in Venture Source startups. Finally, I undertake several robustness checks and find consistently statistically and economically significant results.

Related literature This paper contributes to a large literature examining the nature of spinouts, parent firms, and the effect of spinouts on their parents. This literature has found that within-industry spinouts leverage knowledge developed at

parent firms (Klepper 2002, Agarwal, Echambadi, et al. 2002). Further, it finds that WSOs are both prevalent and particularly productive and fast-growing compared to non-WSO entrants (Muendler et al. 2012, Baslandze 2019). It also finds that the entry of spinouts is associated with worse firm performance, due to increased competition as well as the loss of key employees (Wezel et al. 2006, Campbell et al. 2012, Agarwal, Campbell, et al. 2013).

Regarding the spawning of spinouts, the literature has emphasized the role of strategic disagreements in the decision to spin out (Klepper and Sleeper 2005, Klepper 2007, Klepper and Thompson 2010). Gompers et al. 2005 also studies Venture Source data, constructing a similar dataset to mine but for an earlier sample period. They focus on the permanent firm-characteristics that lead to the formation of spinouts, whereas I focus on the role of R&D spending choices by the parent firm.

Most relatedly, in a contemporaneous paper Babina and Howell 2019 examines the role of parent firm R&D spending in inducing the formation of employee spinouts. They find evidence of a causal relationship. My results are consistent with their findings. There are several differences in the data used and the approach taken. First, they use administrative data from the Census Bureau. While these data are superior in coverage to Venture Source and Compustat, there are two advantages to my approach. First, VC-funded startups are particularly important in generating productivity growth so it is important to confirm their findings for this type of firm. Second, the Census Bureau did not give them access to data from California or Massachusetts. It is important to confirm their findings for these two states as they have the most private R&D spending in aggregate and per capita terms. In terms of

approach, they have an instrumental variables analysis based on instruments from Bloom et al. 2013. I choose not to use this instrument due to concerns about the exclusion restriction. Of course, this means I cannot directly infer causality from my empirical results. It is worth noting, however, that the IV estimate in Babina and Howell 2019 is five times larger than the OLS estimate and that the authors conclude that their OLS estimates are likely more reflective of the average treatment effect of corporate R&D on spinout formation.

The remainder of this chapter is structured as follows. Section 1.2 discusses the data sources used and sample selection. In Section 1.3, I document the merging of the data sources to construct the main dataset, in particular documenting the procedure used for matching parent firms and spinouts. Section and the empirical analysis.

1.2 Data

VentureSource The data on startups comes from Venture Source (VS), a proprietary dataset containing information on venture capital (VC) firms and VC-funded startups.⁴ I use a subsample of the data for US-based startups founded between 1987 and 2009 which contain information on their founding year. The data cover 24,014 startups, 93,010 financing rounds, and 276,772 individual-firm pairs. For each financing round, the data contain information on valuation, amount raised, and status of the business at the time of the round, such as employment and revenue (with some missing data). Most importantly for this analysis, the data contain

⁴At the start of this project, these data were owned by Dow Jones. They have since been sold to CB insights.

employment biographies for each of the startup’s founders and key employees (C-level, high-ranking executives and managers) and board members. In this regard, Venture Source is unique among VC investment databases. Some summary information about the dataset is contained in Table A3. The dataset is described in detail in Steven N. Kaplan et al. 2002 and Steven Neil Kaplan 2016.

Compustat The data on parent firms comes from Compustat North America Fundamentals Annual, a comprehensive database of fundamental and market information on publicly traded companies. In addition to firm-level data on R&D spending, Compustat contains balance sheet, cash flow, and income statement information (e.g., assets, sales), as well as data on employment, industrial classification, and stock price. I also use information from the Compustat Segments database. I consider the subsample consisting of all firms headquartered in the United States in operation at any point between 1984 and 2006, consisting of 20,534 firms.

NBER-USPTO The data on patents comes from the NBER-USPTO database, which contains comprehensive information on all patents granted in the United States from 1976 to 2006 and comes linked to Compustat. I consider the subsample of patents assigned to US firms, consisting of 1,457,136 patents.

1.3 Construction of spinouts dataset

The first step is to define which startup employees should be classified as founders. The Venture Source data contain information on high level employees and board

members. For the purposes of this study, only those employees whose human capital is crucial to the value proposition of the startup should be considered founders. I therefore restrict attention to employees who (1) have a job title related to the core operations of the firm (Founder, Chief, CEO, CTO or President) and (2) join the startup in its first three years since its founding date. When information on the individual's date of joining the startup is missing, I impute it as the founding date of the startup.⁵

Next, I extract information on previous employment using the employment biography data in VS.⁶ The results of this procedure are summarized in Table 1.1. The top twenty previous employers include several well-known technology firms such as IBM, Microsoft, Cisco Systems, Google, and Intel. Two consulting firms, Andersen Consulting and McKinsey & Company, also make the top twenty. I match these data to the firm name variable in Compustat. This requires the use of string-matching techniques: in particular, firm names must be standardized across databases. I use regular expressions to trim "Inc.", "Corp." and similar strings from each entry. I then look for exact matches. For previous employers in VS that do not match with any names in Compustat, I check against the business segment names, available from the Compustat Segments database.

Having linked startups to their founders' previous employers, the next step is to determine which of these startups compete with the parent firm. I accomplish this by using industrial classification as a proxy for product market.⁷ Compustat

⁵Table A1 shows a breakdown of the most frequent job titles.

⁶VS biographies are text fields in a structured format, allowing parsing by regular expressions.

⁷VS does include a "Competition" variable listing competitors. However, this variable is only available for about 20% of startups.

Employer	Count	Employer	Count
IBM	174	Stanford University	56
Microsoft	168	Lucent Technologies	46
Cisco Systems	122	AOL	44
Oracle	109	Motorola	42
Verizon	101	Andersen Consulting	40
Sun Microsystems	94	Nortel Networks	40
Google	79	MIT	40
AT&T	76	McKinsey & Company	39
Intel	70	Texas Instruments	38
Hewlett-Packard	64	Apple	37

Table 1.1: Top 20 previous employers for founders in VS data.

includes data on the self-reported NAICS industry of the parent firms. On the other hand, VS does not contain self-reported NAICS codes. However, it does document industry using a proprietary industry classification whose categories, for the most part, have the same names as corresponding NAICS 4- or 5-digit categories. For the categories which do not have a direct counterpart in NAICS, I look for the 4-digit NAICS category that coincides most in terms of the meaning of the category. Using these industrial classifications, I identify a founder-startup as a WSO whenever the startup is in the same 4-digit NAICS category as its parent.

Following this procedure, approximately 20% of startup founders are matched to a public firm in Compustat. Of these, one third came from an employer in the same four digit NAICS industry as the startup. The remaining 80% were either most recently employed at a firm that is not publicly traded, and so is excluded from Compustat, or the the match failed. Match failure can result for two main reasons.

First, many business segments are not included in the Compustat Segments database. Second, the name standardization procedure is likely imperfect.

Figure 1.1 documents the joint distribution of parent industry and child industry, defined by 2-digit NAICS codes for easier visualization. Because the raw joint distribution is too heavily concentrated in certain industries to be easily visualized in this way, I instead show the conditional distribution of child industry (column) conditional on parent industry (row). The dark diagonal line reflects the prevalence of WSOs. The diagonal entries are particularly intense in industries 32-33 (manufacturing) and 51 (information, which includes software publishing).⁸ This is consistent with the hypothesis that R&D is associated with within-industry spinout formation, as these industries conduct 85% of R&D during the sample period. Figure B1 shows the joint distribution the other way around, with the probability of parent industry conditional on child industry.⁹ The match is further documented in Table A4, which corresponds roughly to Table 1 of Gompers et al. 2005.¹⁰

⁸Appendix Table A2 contains the names corresponding to all two-digit NAICS codes.

⁹In Figure 1.1, the dark vertical line at column 51 (Information) indicates that parent firms of all industries tend to spawn spinouts in that industry. Similar dark regions appear at columns 54 (Professional, Scientific and Technical Services), and 32 and 33 (Manufacturing). In Figure B1, the dark horizontal lines at 51 and to a lesser extent 32, 33, 52 and 54 indicate that child firms of all industries tend to have founders from those industries.

¹⁰I do not exactly replicate their match. My algorithm finds fewer matches early in the sample period and more matches later in their sample period, but always a smaller fraction of total founders. One factor to consider is that startups are only added to the data after they raise venture capital funding for the first time, but may have been founded years earlier.

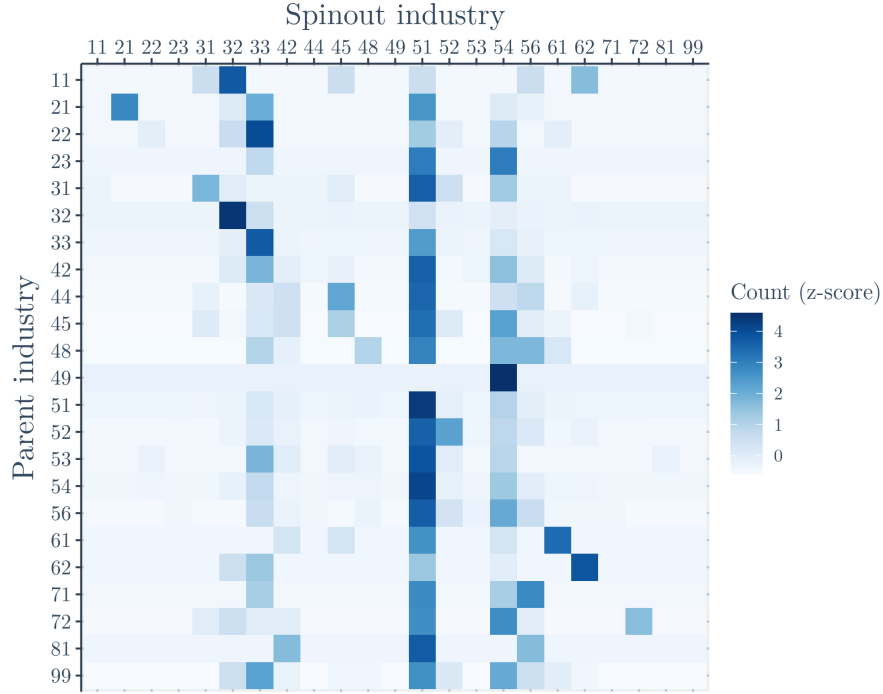


Figure 1.1: Heatmap displaying the distribution of child 2-digit NAICS code (column), conditional on parent NAICS code (row). Darker hues indicate a higher number of founders. To facilitate visualization, counts are normalized to have mean zero and unit standard deviation at the Parent NAICS level.

1.4 Characteristics of within-industry spinouts

In this section I show that there are statistically and economically significant differences between WSOs and non-WSO startups. This is an important component of an adequate quantification of the effect of a given employee founder departure to found a WSOs on both the parent firm and the aggregate economy. In particular, I ask whether WSOs are larger than non-WSOs on a per-founder basis, considering several metrics of size (employment, revenue, and valuation). I also consider IPO and acquisition rates, as well as the rate of business exit. To quantify the extent to which a given

startup is a WSO, I measure the fraction of its founders who were most recently employed at a firm in the same 4-digit NAICS industry. In the end, I find that WSOs are larger along every dimension than non-WSOs. They are also more likely to be acquired and less likely to go out of business.

To begin, Tables 1.2, 1.3, and 1.4 document the relative per-founder log employment, revenue, and valuation of WSOs versus non-WSO startups, revealing that WSOs have a statistically and economically significant advantage along these metrics. In each table, the first column shows the raw comparison while the next three columns show the comparison subject to a battery of fixed effects. In the case of employment and valuation, the relationship is positive and economically significant both with and without fixed effects, though not statistically significant in the case of employment. However, for revenue, in the raw comparison actually WSOs tend to be smaller per founder than non-WSOs. Finally, once I control for industry, state, time, cohort, and / or age fixed effects,¹¹ the per-founder size advantage of WSOs is statistically and economically significant along all dimensions. It is also quite robust across various specifications of fixed effects. Overall, I find that startups with a higher fraction of WSO4 founders tend to have roughly 35% higher employee count, 45% higher revenue, and 36% higher valuation on a per-founder basis.

To complement these findings, Tables 1.5 and 1.6 show that startups with a higher fraction of founders from the same industry are significantly less likely to go out of business and more likely to be acquired or IPO. Again, in both tables the first column shows the raw comparison while the next three columns go through the same sequence

¹¹I control for two of the three (time, cohort, age) factors, to avoid the well-known multicollinearity problem.

	(1)	(2)	(3)	(4)
<u>WSO4 founders</u>	0.20	0.32***	0.32***	0.30***
Total founders	(0.18)	(0.023)	(0.025)	(0.031)
State-Year FE	No	Yes	Yes	No
State-Age FE	No	Yes	No	Yes
State-Cohort FE	No	No	Yes	Yes
NAICS4-Year FE	No	Yes	Yes	No
NAICS4-Age FE	No	Yes	No	Yes
NAICS4-Cohort FE	No	No	Yes	Yes
Clustering	State, Industry	State, Industry	State, Industry	State, Industry
R-squared (adj.)	0.00063	0.38	0.41	0.39
R-squared (within, adj)	0.00063	0.0025	0.0025	0.0023
Observations	54424	53509	53311	53425

Standard errors in parentheses

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

Table 1.2: Dependent variable is the logarithm of the number of employees while the independent variable is the fraction of founders who most recently worked at a public firm in the same industry. The first column shows the raw regression. The following three columns control for state, industry, time, cohort and age factors. Specifically, each regression uses a subset of two of the three (year,age,cohort) effects. Further, these fixed effects are (separately) interacted with state and industry. I use multiway clustering at the state and industry levels.

of fixed effect specifications. In both cases, the raw comparison shows that WSOs are statistically and economically significantly better off than non-WSOs: they are 0.17 percentage points less likely to go out of business each year and 2.52 percentage points more likely to be acquired or IPO. Once fixed effects are added, the former results are amplified while the latter are somewhat curtailed. In particular, WSOs are roughly half of a percentage point less likely to go out of business each year and 2 percentage points more likely to be acquired or IPO each year.

	(1)	(2)	(3)	(4)
<u>WSO4 founders</u>	-0.13	0.45***	0.42***	0.39***
Total founders	(0.094)	(0.13)	(0.081)	(0.12)
State-Year FE	No	Yes	Yes	No
State-Age FE	No	Yes	No	Yes
State-Cohort FE	No	No	Yes	Yes
NAICS4-Year FE	No	Yes	Yes	No
NAICS4-Age FE	No	Yes	No	Yes
NAICS4-Cohort FE	No	No	Yes	Yes
Clustering	State, Industry	State, Industry	State, Industry	State, Industry
R-squared (adj.)	0.000092	0.30	0.38	0.39
R-squared (within, adj)	0.000092	0.0030	0.0026	0.0022
Observations	16948	15500	15531	15905

Standard errors in parentheses

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

Table 1.3: Dependent variable is the logarithm of annual revenue while the independent variable is the fraction of founders who most recently worked at a public firm in the same industry. The first column shows the raw regression. The following three columns control for state, industry, time, cohort and age factors. Specifically, each regression uses a subset of two of the three (year,age,cohort) effects. Further, these fixed effects are (separately) interacted with state and industry. I use multiway clustering at the state and industry levels.

	(1)	(2)	(3)	(4)
<u>WSO4 founders</u> Total founders	0.46*** (0.065)	0.42*** (0.058)	0.36*** (0.069)	0.33*** (0.074)
State-Year FE	No	Yes	Yes	No
State-Age FE	No	Yes	No	Yes
State-Cohort FE	No	No	Yes	Yes
NAICS4-Year FE	No	Yes	Yes	No
NAICS4-Age FE	No	Yes	No	Yes
NAICS4-Cohort FE	No	No	Yes	Yes
Clustering	State, Industry	State, Industry	State, Industry	State, Industry
R-squared (adj.)	0.0042	0.28	0.29	0.26
R-squared (within, adj)	0.0042	0.0050	0.0035	0.0028
Observations	26504	25174	25027	25337

Standard errors in parentheses

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

Table 1.4: Dependent variable is the logarithm of post-money valuation while the independent variable is the fraction of founders who most recently worked at a public firm in the same industry. The first column shows the raw regression. The following three columns control for state, industry, time, cohort and age factors. Specifically, each regression uses a subset of two of the three (year,age,cohort) effects. Further, these fixed effects are (separately) interacted with state and industry. I use multiway clustering at the state and industry levels.

	(1)	(2)	(3)	(4)
<u>WSO4 founders</u>	-0.17*	-0.57***	-0.52***	-0.54***
Total founders	(0.091)	(0.095)	(0.11)	(0.10)
State-Year FE	No	Yes	Yes	No
State-Age FE	No	Yes	No	Yes
State-Cohort FE	No	No	Yes	Yes
NAICS4-Year FE	No	Yes	Yes	No
NAICS4-Age FE	No	Yes	No	Yes
NAICS4-Cohort FE	No	No	Yes	Yes
Clustering	State, Industry	State, Industry	State, Industry	State, Industry
R-squared (adj.)	0.0000013	0.031	0.033	0.018
R-squared (within, adj)	0.0000013	0.000057	0.000043	0.000046
Observations	240155	239696	239788	239959

Standard errors in parentheses

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

Table 1.5: Dependent variable is the annual hazard rate (%) of going out of business while the independent variable is the fraction of founders who most recently worked at a public firm in the same industry. The first column shows the raw regression. The following three columns control for state, industry, time, cohort and age factors. Specifically, each regression uses a subset of two of the three (year,age,cohort) effects. Further, these fixed effects are (separately) interacted with state and industry. I use multiway clustering at the state and industry levels.

	(1)	(2)	(3)	(4)
<u>WSO4 founders</u> Total founders	2.52*** (0.056)	2.19*** (0.14)	2.03*** (0.18)	2.01*** (0.18)
State-Year FE	No	Yes	Yes	No
State-Age FE	No	Yes	No	Yes
State-Cohort FE	No	No	Yes	Yes
NAICS4-Year FE	No	Yes	Yes	No
NAICS4-Age FE	No	Yes	No	Yes
NAICS4-Cohort FE	No	No	Yes	Yes
Clustering	State, Industry	State, Industry	State, Industry	State, Industry
R-squared (adj.)	0.00046	0.035	0.033	0.035
R-squared (within, adj)	0.00046	0.00034	0.00027	0.00027
Observations	240155	239696	239788	239959

Standard errors in parentheses

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

Table 1.6: Dependent variable is the annual hazard rate (%) of a successful exit (IPO, acquisition) while the independent variable is the fraction of founders who most recently worked at a public firm in the same industry. The first column shows the raw regression. The following three columns control for state, industry, time, cohort and age factors. Specifically, each regression uses a subset of two of the three (year,age,cohort) effects. Further, these fixed effects are (separately) interacted with state and industry. I use multiway clustering at the state and industry levels.

1.5 Corporate R&D and spinout formation

In this section I document the empirical relationship between R&D spending and employee spinout formation. These results will motivate and inform the quantitative structural analysis in Chapter 2.

1.5.1 Preliminaries

Figure 1.2 visualizes the relationship between corporate R&D and spinout formation in a binned scatterplot at the parent firm-year level. On the horizontal axis is average

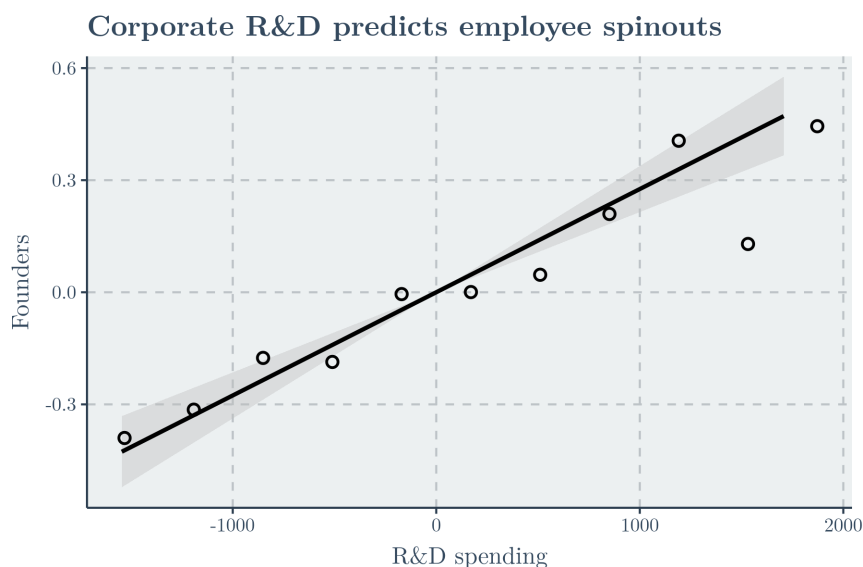


Figure 1.2: Scatterplot of average yearly founder counts (restricted to same 4-digit NAICS industry) in $t+1, t+2, t+3$ versus average yearly R&D spending in $t, t-1, t-2$. R&D spending is measured in millions of 2012 dollars (using the R&D deflator) and additionally deflated by productivity growth (also with 2012 as the base year). Finally, both R&D and founder counts are demeaned at the firm and industry-state-age-year levels.

yearly real effective R&D spending by the parent firm in years $t - 2, t - 1, t$ and on the vertical axis is the yearly number of employees founding startups in years $t + 1, t + 2, t + 3$.¹² Both variables are also demeaned at the firm level and then at the state-industry-age-year level, with industries defined as 4-digit NAICS codes. The solid line shows the best fit of a straight line through the underlying scatterplot. This suggests that firm-level deviations of R&D are associated with future employee spinout formation.

1.5.2 Regressions

To properly assess the statistical significance of this relationship, as well as to control for other confounding factors, I conduct a regression analysis. The main challenge to identification is that time-varying firm-level variables that are not constant at the state-industry-age-year level could be associated with both R&D spending and spinout formation in both positive and negative ways. For example, investment opportunities specific to the firm’s idiosyncratic technological niche would induce R&D spending and potentially within-industry spinout formation by its employees pursuing related ideas. On the other hand, poor management or other tribulations at the parent firm could reduce R&D spending and simultaneously induce employees to found competing firms.

To control for such factors, I include time-varying firm controls. Specifically, I control for employment, cumulative patents, assets, intangible assets, net income,

¹²Real effective R&D spending is calculated from nominal R&D spending by first deflating using the R&D deflator and then further deflating by an index of cumulative productivity growth. This reflects the assumption that a given rate of R&D spending to GDP generates a given flow of new firms. This will be the assumption in the model developed later in the paper.

sales, capital expenditures, and Tobin’s Q ¹³. Consistent with the demeaning in the scatter plot, I include fixed effects at the firm, state-year, industry-year, and age of the firm.¹⁴

Table 1.7 displays the results of the regression analysis. The first column is the regression in levels, given by

$$WSO_{it} = \beta R\&D_{it} + \gamma X_{it} + \alpha_i + \xi_{j(i)t} + \sigma_{s(i)t} + \eta_{a(i,t)} + \epsilon_{it}, \quad (1.1)$$

where i and t index firm and year, $j(i)$ and $s(i)$ are the industry and state of firm i , and $a(i, t)$ is the age of firm i in year t . As in the scatterplot, the dependent variable WSO_{it} is the (annualized) number of founders previously employed at firm i joining startups in years $t + 1, t + 2, t + 3$. $R\&D_{it}$ and the firm controls X_{it} are calculated as moving averages over years $t, t - 1, t - 2$. For clarity, the units of $R\&D_{it}$ are in billions. The parameters $\alpha_i, \xi_{j(i)t}, \sigma_{s(i)t}, \eta_{a(i,t)}$ represent the firm, industry-year, state-year and age fixed effects, respectively. Standard errors are multiway clustered at the state and four-digit industry levels.

The result is statistically significant at the 1% level. The point estimate of 0.24 is quantitatively consistent with the slope of the line in the binned scatterplot in Figure 1.2. The robustness of the result to the inclusion of controls and firm, age, industry-year, and state-year fixed effects is encouraging. However, because the specification is in levels, industry-year, state-year and age fixed effects may be unable

¹³In the regression in levels, I control instead for the firm market value; that is, Tobin’s Q times assets.

¹⁴I do not consider state-industry-age-year fixed effects, as in the scatterplot, because this substantially reduces statistical power.

	(1) WSO4	(2) WSO4	(3) WSO4	(4) WSO4
R&D	0.24*** (0.053)			
log(R&D)		0.47*** (0.072)	1.84*** (0.17)	0.83*** (0.29)
Firm FE	Yes	Yes	No	Yes
Age FE	Yes	No	No	Yes
Industry-Age FE	No	Yes	No	No
Industry-Year FE	Yes	Yes	No	Yes
State-Year FE	Yes	Yes	No	No
Controls	Yes	No	Yes	Yes
Clustering	Industry, State	Firm	Firm	Firm
R-squared (adj.)	0.61			
R-squared (within, adj)	0.23			
pseudo R-squared		0.34	0.47	0.35
Observations	56961	4254	7049	471

Standard errors in parentheses

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

Table 1.7: The regressions above relate corporate R&D to the entrepreneurship decisions of employees. The dependent variable is average yearly number of founders joining startups in years $t + 1, t + 2, t + 3$. The independent variables are averages over $t, t - 1, t - 2$. Firm controls are employment, assets, intangible assets, investment, sales, net income, cumulative patents (weighted by all future citations), and firm market value (column 1) or Tobin's Q (columns 2-4).

to control for unobservable time-varying confounding factors. Intuitively, in a levels specification each fixed effect is restricted to be constant for all in the corresponding fixed effect cell. However, time-varying industry- or state-level shocks that encourage both R&D spending and spinout formation are likely to affect firm outcomes more in absolute terms for larger firms.

To address this concern, the next three columns of Table 1.7 show the results of Poisson pseudo-Maximum Likelihood (PPML) regressions, with a specification of

$$WSO_{it} = \exp \left\{ \beta \log R\&D_{it} + \gamma x_{it} + \alpha_i + \xi_{j(i)t} + \sigma_{s(i)t} + \eta_{a(i,t)} \right\} + \epsilon_{it}, \quad (1.2)$$

where x_{it} denotes the logarithm of the firm-level controls. This specification can be thought of as a log-linear regression which can handle zeros in the dependent variable. It is also the specification in the model, as the rate of employee departures is assumed to depend on R&D spending following a Poisson process.¹⁵ In this specification, the industry-year, state-year and age fixed effects have a proportional effect on the formation of WSOs. This should allow them to better proxy for such unobservable effects which are correlated with R&D and spinout formation and hence can bias the results of the levels regression. I perform three regressions with this specification: one with controls, but no fixed effects (column 2); one with fixed effects but no controls (column 3); and one with both controls and fixed effects (column 4). In all cases, in order to have sufficient clusters, I cluster standard errors by firm rather than by industry and state as in the levels regression.

¹⁵Even if Poisson is not the correct specification, the PPML specification consistently estimates the conditional mean of the actual distribution.

In all three regressions the coefficient on the logarithm of R&D spending is statistically significant at the 1% level. The coefficient on R&D spending corresponds to an elasticity of spinout formation to R&D spending. In column 2, which has no controls but includes firm, industry-age, industry-year, and state-year fixed effects, the the estimate corresponds to an elasticity of 0.47. This conforms to the elasticities estimated in the micro literature for other outputs of R&D, such as patents.¹⁶ In column 3, which uses no fixed effects but includes the full set of firm controls, the estimate corresponds to an elasticity of 1.84. Finally, the estimate in column 3 uses both controls and fixed effects, exchanging industry-age fixed effects for age fixed effects in order to lose fewer observations. The estimate in this case corresponds to an elasticity of 0.83, somewhat less precisely estimated than the previous two due to the smaller sample size.

Next, I provide some suggestive evidence that industry-year and state-year correlated shocks are not driving the results in the original specification. Tables Table 1.8 and Table 1.9 show that including firm age, industry-year, and state-year fixed effects in the PPML regression does not reduce the coefficient estimate on the logarithm of R&D. In fact, when controls are not included, going from only firm fixed effects to the full set of fixed effects increases the estimate slightly increases from 0.4 to 0.47. When controls are included, the estimate increases dramatically from 0.5 to 2.17, although this may be due to the fact that many observations are dropped. These results suggest that correlated industry-year, state-year and firm age shocks to R&D and spinout formation are not responsible for the correlation between R&D and

¹⁶See Akcigit and Kerr 2018 for a discussion.

	(1)	(2)	(3)	(4)
	WSO4	WSO4	WSO4	WSO4
log(R&D)	0.40*** (0.044)	0.52*** (0.067)	0.44*** (0.062)	0.47*** (0.072)
Firm FE	Yes	Yes	Yes	Yes
Industry-Age FE	No	Yes	Yes	Yes
Industry-Year FE	No	No	Yes	Yes
State-Year FE	No	No	No	Yes
Clustering	Firm	Firm	Firm	Firm
pseudo R-squared	0.28	0.31	0.33	0.34
Observations	5308	4928	4784	4254

Standard errors in parentheses

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

Table 1.8: Robustness of PPML regression without controls to adding industry-age, industry-year, and state-year fixed effects. Clustering is at the firm level to ensure sufficient clusters.

WSO formation. However, without exogenous variation in R&D, I cannot definitively rule out the possibility that the problematic shocks operate at a more granular level.

Note that I do not pursue an instrumental variables strategy to induce exogenous variation in R&D spending. The natural candidate for an instrumental variable in this case described in Bloom et al. 2013, which is driven by exogenous variation in R&D subsidies. However, its variation is largely driven by R&D tax incentives at the state-level. This means the instrument likely fails to satisfy the exclusion restriction, as WSO formation may also respond to tax incentives in the same way. Nevertheless, the instrument is considered in Babina and Howell 2019, where the authors argue that R&D tax incentives play little role in startup formation, as they are implemented as a

	(1)	(2)	(3)	(4)
	WSO4	WSO4	WSO4	WSO4
log(R&D)	0.50 (0.34)	0.51** (0.26)	0.83*** (0.29)	2.17** (0.90)
Firm FE	Yes	Yes	Yes	Yes
Age FE	No	Yes	Yes	Yes
Industry-Year FE	No	No	Yes	Yes
State-Year FE	No	No	No	Yes
Clustering	Firm	Firm	Firm	Firm
pseudo R-squared	0.33	0.35	0.35	0.36
Observations	630	625	471	279

Standard errors in parentheses

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

Table 1.9: Robustness of PPML regression with controls to adding industry-age, industry-year, and state-year fixed effects. Clustering is at the firm level to ensure sufficient clusters.

corporate income tax credit. While such credits can be carried forward twenty years, this only has future value in the event that the startup is profitable and therefore pays taxes, reducing the present value of the tax incentive. In any case, the IV estimate they obtain is five times larger than their OLS estimate and the latter is the authors' preferred estimate of the average treatment effect of R&D spending on spinout formation.¹⁷

To assess the economic magnitude of the relationship between R&D spending and WSO formation, I use the estimate in column 1 to construct an estimate of the fraction of WSO founders in the data that can be accounted for by R&D spending.

¹⁷They argue that the discrepancy could be because the IV is capturing a local average treatment effect (LATE), where marginal R&D spending is more likely to lead to spinout formation because it is less closely related to the firm's core business.

In each year t , I compute $\hat{WSO}_t$, the expected number of within-industry spinout founders induced by R&D per year over the years $t + 1, t + 2, t + 2$, by multiplying average aggregate real effective R&D spending in years $t, t - 1, t - 2$ by the coefficient estimates from column 1. I then aggregate across years in the sample. Based on this measure, the regression coefficient is economically significant: it can account for 85% of the WSO spinout founders observed in the data, who in turn account for 7% of all founders.¹⁸ Combining these findings with the fact that WSOs tend to be about 40% larger per-founder means that R&D-induced WSOs can account for about 8.5% of the level of employment, revenue and valuation of startups in the dataset.

1.6 Conclusion

This chapter provides empirical evidence in support of two hypotheses. First, that within-industry spinout formation is an important source of particularly productive startups. Second, that such firms form in part as a byproduct of R&D spending at the parent firm.

It first shows that WSOs are typically about 40% larger than equivalent non-WSO startups in terms of employment, revenue, and valuation per founder. This suggests that WSO founders are more productive than non-WSO founders. It also finds similar results regarding the likelihood of business failure and of IPOs and

¹⁸Figure B2 shows a similar accounting exercise using data at the industry-year level, focusing on NAICS industries 3 (manufacturing) and 5 (information), which are responsible for the vast majority of private sector R&D spending. The pattern is clearly different by industry, with a very good fit for manufacturing industries but underestimated spinouts in information industries. A framework that is able to account for variation in this mechanism across industries would therefore be useful in future work.

acquisitions, suggesting that WSOs are more productive than non-WSOs. These two findings support the first hypothesis described above that WSOs are on average more productive than ordinary startups.

Next, it shows that R&D tends to predict employee spinout formation at the firm level, after controlling for firm level variables and various fixed effects. The relationship is statistically and economically significant, accounting for about 8.5% of employment in the Venture Source data. These results are consistent with previous findings in Babina and Howell 2019 and Muendler et al. 2012, respectively, in a dataset of publicly traded parent firms and venture-capital financed startups. This is important as publicly traded firms conduct the majority of R&D and VC-funded startups are particularly important contributors to aggregate productivity growth.

The analysis in this chapter shows that the data are consistent with an economically significant effect of corporate R&D spending on within-industry spinout formation. While the absence of exogenous variation in R&D prevents a definitive conclusion regarding causality, the evidence is sufficient to motivate the analysis in Chapter 2 of the potential aggregate implications of this mechanism. Beyond this, there are two primary directions for future work. First, it may be fruitful to analyze the relationship between R&D spending and WSO formation separately by industry. Second, it is important to study the extent to which the within-industry spinouts identified here compete with or complement their parent firms.

References

- Agarwal, Rajshree, Benjamin A. Campbell, et al. (Apr. 1, 2013). *What Do I Take with Me?: The Mediating Effect of Spin-Out Team Size and Tenure on the Founder-Firm Performance Relationship*. SSRN Scholarly Paper ID 2247653. Rochester, NY: Social Science Research Network.
- Agarwal, Rajshree, Raj Echambadi, et al. (Feb. 1, 2002). “Knowledge Transfer through Congenital Learning: Spin-Out Generation, Growth and Survival”.
- Akcigit, Ufuk and William R. Kerr (Mar. 2018). “Growth through Heterogeneous Innovations”. *Journal of Political Economy* 126.4, pp. 1374–1443.
- Babina, Tania and Sabrina T Howell (July 2019). “Entrepreneurial Spillovers from Corporate R&D”. *NBER Working Paper*, p. 76.
- Baslandze, Salome (2019). “Spinout Entry, Innovation, and Growth”. *Working Paper*.
- Bloom, Nicholas, Mark Schankerman, and John van Reenen (2013). “Identifying Technology Spillovers and Product Market Rivalry”. *Econometrica* 81.4, pp. 1347–1393.

- Campbell, Benjamin A. et al. (2012). “Who leaves, where to, and why worry? employee mobility, entrepreneurship and effects on source firm performance”. *Strategic Management Journal* 33.1, pp. 65–87.
- Franco, April Mitchell and Darren Filson (Dec. 2006). “Spin-outs: knowledge diffusion through employee mobility”. *The RAND Journal of Economics* 37.4, pp. 841–860.
- Gompers, Paul, Josh Lerner, and David Scharfstein (2005). “Entrepreneurial Spawning: Public Corporations and the Genesis of New Ventures, 1986 to 1999”. *The Journal of Finance* 60.2, pp. 577–614.
- Kaplan, Steven N., Berk M. Sensoy, and Per Stromberg (Sept. 2002). “How well do venture capital databases reflect actual investments?” *Working Paper*.
- Kaplan, Steven Neil (2016). “Venture Capital Data: Opportunities and Challenges”. *NBER Working Paper*, p. 26.
- Klepper, Steven (Aug. 1, 2002). “The capabilities of new firms and the evolution of the US automobile industry”. *Industrial and Corporate Change* 11.4. Publisher: Oxford Academic, pp. 645–666.
- (Apr. 2007). “Disagreements, Spinoffs, and the Evolution of Detroit as the Capital of the U.S. Automobile Industry”. *Management Science* 53.4, pp. 616–631.
- Klepper, Steven and Sally Sleeper (Aug. 2005). “Entry by Spinoffs”. *Management Science* 51.8, pp. 1291–1306.

- Klepper, Steven and Peter Thompson (Sept. 1, 2010). “Disagreements and intra-industry spinoffs”. *International Journal of Industrial Organization* 28.5, pp. 526–538.
- Muendler, Marc-Andreas, James E. Rauch, and Oana Tocoian (Sept. 2012). “Employee spinoffs and other entrants: Stylized facts from Brazil”. *International Journal of Industrial Organization* 30.5, pp. 447–458.
- Werth, Barry (Feb. 2014). *The Antidote: Inside the World of New Pharma*. New York, NY: Simon & Schuster.
- Wezel, Filippo Carlo, Gino Cattani, and Johannes M. Pennings (Dec. 1, 2006). “Competitive Implications of Interfirm Mobility”. *Organization Science* 17.6. Publisher: INFORMS, pp. 691–709.

Appendix

1.A Appendix of tables

Title	Individuals	Percentage
Chief Executive Officer	11154	25.3
Chief Technology Officer	8493	19.2
President & CEO	7965	18.0
Chief	5893	13.3
President	4118	9.3
Founder	3000	6.8
Chairman & CEO	2439	5.5
President & COO	982	2.2
President & Chairman	105	0.2

Table A1: Most frequent titles among key founders in VS data.

NAICS Code	Description
11	Agriculture, Forestry, Fishing and Hunting
21	Mining, Quarrying, and Oil and Gas Extraction
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale trade
44-45	Retail trade
48-49	Transportation and warehousing
51	Information
52	Finance and insurance
53	Real estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative, Support, Waste Management, Remediation Service
61	Educational services
62	Health Care and Social Assistance
71	Arts, Entertainment, Recreation
72	Accommodation and Food Services
81	Other Services (except public Admin.)
92	Public Administration

Table A2: 2-digit NAICS codes summary

Industry	Startups	Individuals	State	Startups	Individuals	Year	Startups	Individuals
Business Applications Software	1890	24572	California	8921	110208	1987	353	2680
Biotechnology Therapeutics	1089	14381	Massachusetts	2279	30536	1988	356	2831
Communications Software	1036	13387	New York	1644	16896	1989	403	3247
Advertising/Marketing	962	12004	Texas	1372	15324	1990	396	3159
Network/Systems Management Software	688	10866	Pennsylvania	927	8906	1991	422	3751
Vertical Market Applications Software	561	7065	Washington	827	9647	1992	537	4854
Online Communities	550	3984	Colorado	637	7592	1993	554	5294
Application-Specific Integrated Circuits	464	6202	Virginia	618	7670	1994	689	6735
IT Consulting	461	5482	Georgia	579	6420	1995	876	8910
Wired Communications Equipment	454	6651	Illinois	573	5981	1996	1191	13102
Drug Development Technologies	412	5038	New Jersey	567	6560	1997	1141	13426
Healthcare Administration Software	403	4978	Florida	559	5277	1998	1513	19471
Therapeutic Devices (Minimally Invasive/Noninvasive)	374	4668	North Carolina	466	5326	1999	2557	32463
Fiberoptic Equipment	364	4911	Maryland	437	5230	2000	2003	24251
Database Software	357	4500	Minnesota	378	4093	2001	1067	13268
Business Support Services: Other	341	3889	Ohio	375	2911	2002	986	12928
Multimedia/Streaming Software	337	4066	Connecticut	367	3727	2003	1037	11912
Entertainment	335	2555	Utah	255	2570	2004	1110	13345
Procurement/Supply Chain	327	4744	Oregon	224	2415	2005	1222	13305
Wireless Communications Equipment	322	4506	Tennessee	222	2134	2006	1380	13823
Specialty Retailers	308	2915	Arizona	211	2280	2007	1506	13045
Pharmaceuticals	301	3629	Michigan	209	1707	2008	1416	10469
Data Management Services	292	4034	Wisconsin	142	1110	2009	1494	9460

Table A3: Statistics on startups covered by VS sample. The first three columns disaggregate by industry, the second three by state, and the last three by year. Industry information uses VS industrial classification. Startups are counted by founding year, individuals by year they joined the firm.

Year	Number founders	of	Number start-ups	of	Number founders from public companies	Fraction from public companies (%)	Fraction from public companies when bio. info available (%)	Fraction from public companies in same 4-digit NAICS (%)	Fraction from public companies in same 4-digit NAICS when bio. info available (%)
1986	269		216		45	16.7	22.8	5.2	7.1
1987	356		280		43	12.1	15.1	3.9	4.9
1988	372		281		58	15.6	19.9	4.6	5.8
1989	479		341		75	15.7	19.2	4.2	5.1
1990	478		329		85	17.8	21.1	6.3	7.5
1991	540		356		81	15.0	17.9	6.3	7.5
1992	674		450		100	14.8	17.9	3.3	3.9
1993	778		490		137	17.6	20.3	6.7	7.7
1994	999		611		167	16.7	19.3	4.9	5.7
1995	1326		772		224	16.9	19.0	5.2	5.8
1996	1926		1077		319	16.6	18.1	4.9	5.3
1997	1986		1036		345	17.4	19.0	5.9	6.5
1998	2895		1390		541	18.7	19.6	5.2	5.5
1999	5189		2388		975	18.8	19.6	5.0	5.2
2000	4084		1832		786	19.2	20.4	5.2	5.5
2001	2245		948		384	17.1	18.7	6.3	6.9
2002	2113		884		385	18.2	20.1	7.3	8.0
2003	1979		903		344	17.4	19.8	7.5	8.5
2004	2098		988		365	17.4	20.1	6.8	7.9
2005	2278		1068		400	17.6	20.7	6.5	7.7
2006	2492		1212		432	17.3	20.5	6.3	7.5
2007	2817		1366		388	13.8	17.0	4.9	6.1
2008	2710		1307		422	15.6	19.1	5.4	6.6

Table A4: Summary of founders. Here, "founder" includes all individuals employed at startups in the VentureSource database who (1) joined the startup within 3 year(s) of its founding year; and (2) have the title of CEO, CTO, CCEO, PCEO, PRE, PCHM, PCOO, FDR, CHF.

1.B Appendix of figures

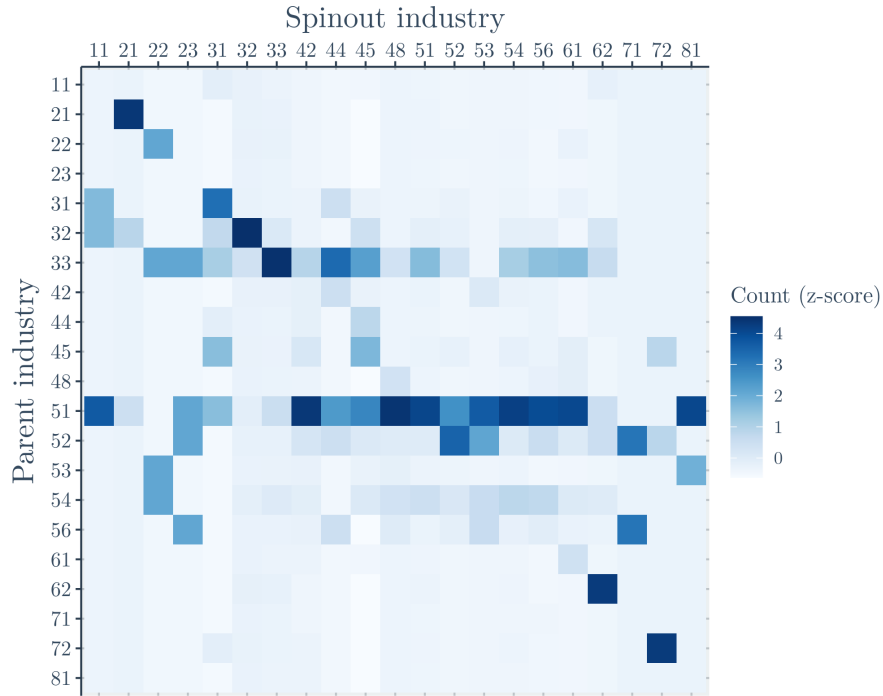


Figure B1: Heatmap displaying the distribution of parent 2-digit NAICS code (row), conditional on child NAICS code (column). Darker hues indicate a higher density. The industries 49 and 99 are omitted because I do not link any startups in those industries to parent firms in Compustat.

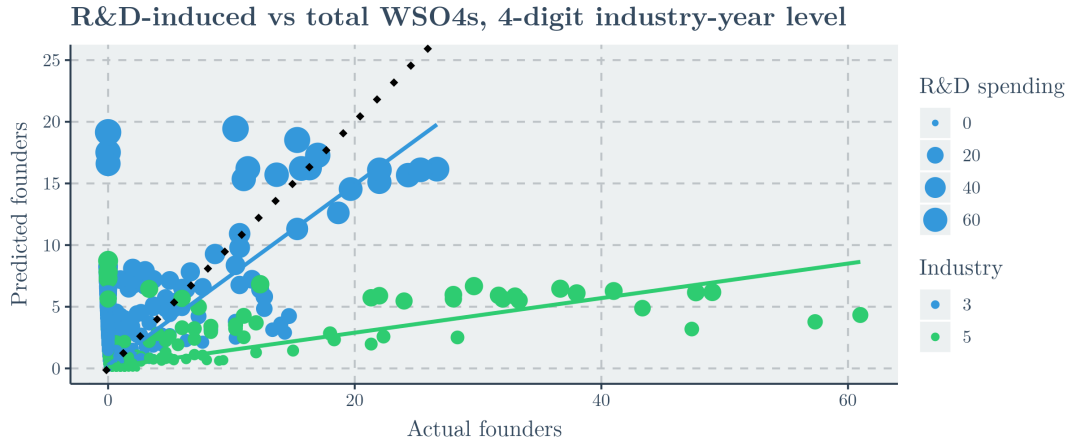


Figure B2: Economic magnitude of regression estimates (i.e. using the average value of the coefficient on R&D from the first two columns of Table 1.7). The figure compares predictions for WSO founder counts at the industry-year level (4-digit industries) to the observed number of founders. This plot considers only industries starting with 3 (manufacturing) or 5 (which includes software publishers and professional services), which together comprise more than 85% of R&D spending in Compustat. The points are color coded by 1-digit NAICS industry. The line in the corresponding color shows the fit of a regression of predicted founders on actual founders. The dotted black line shows the 45 degree line.

Chapter 2

Endogenous Growth with Employee Spinouts, Noncompetes, and Creative Destruction

2.1 Introduction

As shown in the previous chapter, within-industry employee spinout formation is an important source of productive startups. Further, the main result suggests that R&D at the original employer plays a central role in generating WSOs. To avoid competition from WSOs, incumbent may firms reduce their investment in R&D. However, companies often employ an alternative method of protection: noncompete agreements (noncompetes or NCAs). Such agreements have become quite prevalent in the United States in recent years, especially among high-skill workers working in

technical occupations and industries, where the incidence of noncompetes is above 40%.¹

When bound by a noncompete agreement, an employee is legally prohibited from joining or founding a competing firm for a certain time after ceasing his or her current employment. Noncompetes therefore allow employees to commit not to forming spinouts. While this of course inhibits innovation by spinouts, potentially worsening the allocation of the inputs to innovative, it also mitigates the disincentive to undertake R&D for the original employer. This economic tradeoff motivates several questions. What is the effect of noncompetes on aggregate productivity growth? How does this depend on structural parameters that may be different in different locations, industries or time periods? Is it socially optimal to enforce noncompete agreements?

I begin the chapter by developing a model which captures the relationship between R&D and spinout formation found in the analysis of Chapter 1. It consists of a standard general equilibrium model of endogenous growth through creative destruction and own-product innovation augmented to include within-industry spinouts and noncompetes. I assume that the aggregate supply of R&D labor is inelastic, focusing the analysis on its allocation between own-product innovation by incumbent firms and creative destruction by entrants. This assumption also allows for a closed form solution. To incorporate spinout formation, I assume that R&D employees for firms conducting own-product R&D stochastically gain the ability to form a within-industry spinout, replacing the incumbent.

¹See Starr, Prescott, et al. 2019.

To protect against the risk of being displaced by a spinout, incumbents can impose a noncompete on their R&D labor. Using an NCA, however, is not without cost. There is a direct cost, which represents the physical costs of enforcing the contract as well as legal barriers to the use of NCAs (an infinite cost is equivalent to a ban). In addition, in equilibrium, incumbents imposing an NCA must pay an endogenous wage premium in order to induce workers to voluntarily relinquish their right to profit from future spinout formation. In other words, when an NCA is not used, the incumbent implicitly compensates the employee through the expected value to the employee of future spinouts created. Of course, providing this implicit compensation is costly to the incumbent, as it implies a higher risk of losing profits. Incumbents choose whether to use an NCA in order to provide the equilibrium rate of compensation to R&D workers in the least costly way. The result of incumbents and employees optimizing is that NCAs are used exactly when they maximize the bilateral value of R&D employment.

In order for the model to generate a role for NCAs, therefore, there has to be a friction in the employment relationship that implies that, absent an NCA, a bilaterally suboptimal outcome may occur. Otherwise, by the logic in the previous paragraph, NCAs would be redundant. In particular, there is no role for NCAs if incumbents can acquire a bilaterally inefficient employee spinout before it is implemented and then shut it down (or implement it more efficiently inside the firm). This would prevent the bilaterally suboptimal outcome. While this acquisition strategy entails a cost to the incumbent in the event an employee has an idea for a spinout, in equilibrium the employee would accept a lower wage *ex ante* in anticipation of this buyout and,

as a result, the incumbent would behave as though it had imposed a noncompete. To avoid this implication while keeping a simple model, I assume that there is no market in which spinouts can be sold to the incumbent firm that generated them. In reality, such a friction could be caused by asymmetric information concerning the quality of the idea (Chatterjee and Rossi-Hansberg 2012), disagreements between the employee and the employer concerning the idea’s quality (Klepper 2007), or limited commitment on the part of the employee (e.g., the employee cannot commit not to implement the idea even after selling it to his employer). In addition, antitrust law could prevent anticompetitive buyouts. Empirically, Babina and Howell 2019 finds that only 2% of employee-founded firms in Venture Source are bought out by their former employers.²

Importantly, bilaterally inefficient spinouts need not be socially inefficient, as innovation has positive externalities. In addition to the consumer surplus, innovation in one product increases the production efficiency all other producers, as well as the innovation efficiency of entrants. As a result, NCAs can have a negative direct impact on welfare. On the other hand, NCAs can increase growth through their effect on the incentives for R&D by incumbents. In the model, with an inelastic aggregate supply of R&D labor, this shifts R&D labor away from entrants engaging in creative destruction. For certain parameters this increases growth, as entrants are willing to do R&D in equilibrium in spite of less efficient technology. This occurs for two main reasons. First, the payoff per innovation through creative destruction is larger, as it replaces the monopoly of an existing incumbent. This is known as the

²They consider employee-founded firms in Venture Source as identified in Gompers et al. 2005. They do not restrict attention to firms in the same industry as the parent firm.

business-stealing externality. In addition, entrants impose a congestion externality on each other as they attempt similar ideas without coordination.³ Overall, if R&D labor is sufficiently misallocated compared to the social value of within-industry spinout formation, enforcing NCAs can increase the equilibrium growth rate in spite of the fact that it contracts the innovation possibilities frontier.

To quantify the model, I use the estimates from Chapter 1, aggregate statistics (such as the growth rate, interest rates, and profit shares), and innovative growth accounting decompositions from Garcia-Macia et al. 2019 and Klenow and Li 2020. I also choose some parameters from the literature. I then use the model to study the effect on productivity growth and welfare of reducing the direct cost of using NCAs to zero, which I interpret as a relaxation of all legal barriers to their use. I find that growth rises by 0.21 percentage points and welfare rises 3.24% in consumption-equivalent terms. This results from the fact that, in the calibrated equilibrium, the business-stealing externality is strong and therefore R&D is substantially overallocated to creative destruction. Allowing the use of NCAs shifts R&D labor significantly to own-product innovation by incumbent firms. This corrects the equilibrium misallocation, increasing growth sufficiently to compensate for the reduced innovation by spinouts.

Next, I discuss how this result depends on parameters and, via the calibration, on the value of the targeted moments. I also discuss the sensitivity of the result to the parameters chosen externally. I show that the result is quantitatively robust to two plausible model extensions which attenuate it. Finally, I show an alternative calibration in which NCA enforcement reduces welfare and discuss the intuition for

³I model this with a reduced form assumption following Acemoglu and Cao 2015.

why the result is different in that case. In the alternative calibration, the employment share of young firms is lower while all other targets, including the growth share of young firms engaging in creative destruction, is held constant. This implies that each innovation by a new firm must be a larger improvement relative to the previous incumbent's quality. In turn, this implies that a smaller share of the private return to creative destruction is business-stealing, mitigating the equilibrium misallocation of R&D spending. This weakens the growth increase from the reallocation of R&D labor such that growth is maximized by banning NCAs.

Finally, I consider some alternative policies that can substitute or complement the enforcement of NCAs. First, I consider the implications of R&D subsidies in this setting. I find that R&D subsidies can reduce growth by shifting R&D to entrants. In addition, they can induce incumbents to use NCAs when they otherwise would not have. Intuitively, R&D subsidies apply only to R&D wages, not to the cost of losing business to future spinouts. This makes R&D spending on own-product innovation by incumbents more expensive, shifting R&D labor to creative destruction by entrants in equilibrium. It also makes not using an NCA relatively more expensive, since the wage premium associated with using an NCA is subsidized. This induces the use of NCAs. Next, I consider targeted R&D subsidies; that is, subsidies that are only available to incumbent firm engaging in own-product innovation. I find that targeted R&D subsidies can significantly increase growth and improve welfare. However, just as with untargeted R&D subsidies, targeted R&D subsidies induce incumbents to use NCAs. Therefore, I finally consider the combination of targeted R&D subsidies and NCA enforcement policy. I find that the welfare-maximizing (growth-maximizing)

policy is a large targeted R&D subsidy of 95% (88%) combined with a ban on the use of NCAs. However, if targeted R&D subsidies are below 77% (62%), reducing the barriers to the use of NCAs is optimal (growth-maximizing).

Related literature This chapter adds to several strands of the literature. First, and most closely related, is a large literature examining the effect of noncompete contracts on worker mobility, entrepreneurship, incumbent firm investment and productivity growth. Due to the general lack of data on the use of NCAs, the empirical literature has typically exploited variation in the enforceability of noncompetes at the state-level.⁴ In some cases, this variation is argued to be exogenous, either due to legislative error (Marx, Strumsky, et al. 2009, Marx, Singh, et al. 2015) or due to unexpected court outcomes which then serve as judicial precedent (Jeffers 2018). In addition, such papers typically use a diff-in-diff methodology exploiting a control industry that is unaffected by NCA enforcement, usually the legal industry. A survey of this work can be found in Bishara and Starr 2016.

The results from the empirical work are consistent with the economic tradeoff of discussed above. Namely, higher enforcement of NCAs reduces worker mobility and entrepreneurship, but at the same time increases investment by incumbent firms. Regarding the effect on worker mobility, Marx, Strumsky, et al. 2009 finds that inventor mobility declines in response to an exogenous increase in noncompete enforcement. Garmaise 2011 finds that, in states where NCAs are more enforceable, managers are less mobile, have lower compensation, and invest less in their human capital. Balasubramanian et al. 2020 finds that a 2015 ban on technology worker NCAs

⁴I discuss some notable exceptions below.

in Hawaii increased job mobility and worker earnings. In an important qualification, Starr 2018 finds that the negative wage effects associated with high NCA enforceability are driven by states in which workers can be asked to sign an NCA without “due consideration,” consisting of a wage increase or promotion.⁵ Regarding the negative effects on entrepreneurship, Stuart and Sorenson 2003 finds less local entrepreneurship in response to local IPO in states that enforce NCAs. Samila and Sorenson 2010 finds that an increase in VC funding supply increases entrepreneurship more in states without noncompete restrictions. Starr, Balasubramanian, et al. 2018 finds that NCA enforceability is associated with reduced formation of WSOs, in particular preventing the formation of relatively low quality WSOs.

On the other hand, higher NCA enforcement has been found to positively affects investment by incumbent firms. Conti 2014 finds that higher enforceability of NCAs leads incumbent firms to pursue riskier R&D projects. Jeffers 2018 finds that higher enforceability of NCAs increases investment by incumbent firms. In a related finding, Colombo et al. 2013 finds that easier access to startup financing leads to a reduction in incumbent firm knowledge investments.

While examining the effect of state-level differences in NCA enforcement provides valuable insights, some papers point to important qualifications of that approach. Marx, Singh, et al. 2015 returns to the Michigan increase in NCA enforcement and finds evidence of significant brain drain of productive and collaborative inventors towards low-enforcement states in response. This suggests that differences in state-level outcomes by NCA enforceability – such as entrepreneurship and wages – could

⁵The authors suggest that this would allows firms to use NCAs to increase their bargaining power by imposing an NCA after the worker has already rejected other job offers.

reflect reallocation across states of the human capital inputs to entrepreneurship, innovation, and productivity growth. Moreover, recent work has highlighted the importance of using individual-level data on the use of NCAs. Starr, Prescott, et al. 2019 constructs the first nationally representative dataset on the use of noncompetes at the employee level. They find that 20% of employees in the US are bound by an NCA, with substantial heterogeneity across occupations, industries and income groups. In particular, more than 35% of workers in computer, mathematical, architectural, or engineering occupations; more than 30% of workers in the professional, scientific and technical services and information industries; and more than 45% of workers earning more than \$150,000 per year are bound by NCAs. This confirms anecdotal reports about the prevalence of NCAs in the United States. Puzzlingly, however, they find that the incidence of NCAs does not vary significantly with the cross sectional state-level variation in the enforceability of NCAs. In follow up work, Starr, Prescott, et al. 2020 finds that workers bound by NCAs have reduced job mobility, particularly towards competing firms, regardless of the enforceability of NCAs. The reduced mobility is driven by a reduced job search rate in both regimes, while offers from poaching firms are only reduced in enforcing regimes. The authors interpret this as evidence of employee's limited knowledge of the enforceability of NCA contracts. Overall, these results suggest that empirical work exploiting the cross section of NCA enforceability may not be capturing the effect of noncompetes.

This chapter also relates to a literature examining the effect of NCAs on innovation and growth using a structural approach (April M. Franco and Mitchell 2008, Shi 2018, Baslandze 2019). Closest to this paper is the recent work by Baslandze 2019, which

studies the effect of NCAs on spinout entry and growth in a similar framework. She also uses a general equilibrium model of endogenous growth with employee spinouts, using Compustat and NBER-USPTO patent data to discipline the analysis and, in particular, to identify spinouts. There are several important differences. First, as she identifies spinouts using patent data, she focuses on spinouts whose founders patented at both the parent firm and the spinout. Second, her study focuses on all spinouts rather than within-industry spinouts. Thus she empirically considers all spinouts and, in her model, spinouts do not compete with the parent firm. Instead, the harm to the parent firm results from losing a valuable R&D manager who embodies the firm's technological lead over its closest rival. Third, in her model the flow of R&D spending does not lead to the formation of spinouts; rather, it is the stock of knowledge at the firm that makes spinouts formed by the R&D manager more valuable, increasing the incentive of the R&D manager to form a spinout. Finally, she encodes the extent of NCA enforcement as a cost of spinout formation. By contrast, in my model NCAs only reduce the formation of within-industry spinouts and whether they are used is an equilibrium outcome responding to the bilateral inefficiency of spinout formation.⁶

This chapter relates further to a literature examining the interplay of invention, the market for ideas, and the boundaries of the firm (Arrow 1962, Anton and Yao 1994, Anton and Yao 2002, Anton and Yao 1995, April Mitchell Franco and Filson 2006, Chatterjee and Rossi-Hansberg 2012. Anton and Yao 1995 considers how such frictions, in particular the risk of expropriation, can lead to employees forming spinouts rather than implementing their ideas inside the firm. April Mitchell Franco

⁶As noted above, however, I do not explicitly model the source of inefficient creative destruction when there is no NCAs imposed.

and Filson 2006 develops a model in which employees learn from their employers and use this knowledge to form spinouts. Their setting shares with mine the fact that employees implicitly pay for the knowledge they acquire while employed at the parent firm through lower equilibrium wages. However, in their settings spinouts do not directly compete with the parent firm, and further assumptions about the growth process imply that the equilibrium is Pareto efficient. By contrast, in my model, as is standard in the endogenous growth models discussed in the next paragraph, the equilibrium is generally not Pareto efficient due to both positive and negative externalities associated with innovation.

This chapter also relates to the literature on endogenous growth and firm dynamics discussed in Romer 1986, Romer 1990, Grossman and Helpman 1991, and Aghion and Howitt 1992, Klette and Kortum 2004, Lentz and Mortensen 2008, Acemoglu and Cao 2015, Acemoglu, Akcigit, et al. 2018, and Akcigit and Kerr 2018, among others. Most related is Acemoglu, Akcigit, et al. 2018, which examines the role of the allocation of skilled labor in the determination of productivity growth. The main finding is that subsidies to incumbent R&D worsen the allocation of skilled labor by preventing the reallocation to higher productivity entering firms. Their framework is different along two important dimensions. First, they assume incumbents only engage in creative destruction, as in Klette and Kortum 2004 and Lentz and Mortensen 2008. This means that incumbents and entrants are both engaged in business-stealing, eliminating any possibility that business stealing incentives could create a misallocation of R&D spending. Second, they assume that incumbents stochastically enter an absorbing state of low innovation productivity, but still tie up skilled labor that could otherwise

do R&D as they hire executives and managers. Together, these assumptions yield a model in which equilibrium overallocates skilled labor to incumbents that are unproductive at innovation. In my model, by contrast, incumbents are unique in their access to the own-product innovation technology which, due to the lack of business-stealing incentives, is crowded out in equilibrium by relatively inefficient creative destruction. Therefore, there is significant positive growth impact from policies that make own-product innovation by incumbents relatively less expensive.

Finally, this chapter relates to a large literature studying the private and social returns to R&D. The empirical literature includes seminal works such as Griliches 1979, Griliches 1992 and later studies in Nicholas Bloom et al. 2013, Harrison et al. 2014, Mohnen and Hall 2013, and Doraszelski and Jaumandreu 2013. Jones and Williams 1998 and Comin 2004 examine this question using a structural approach. A survey can be found in Hall et al. 2010. This literature has typically found that the social returns to R&D are significantly higher than the private returns. This paper complements this work by emphasizing the heterogeneity of this breakdown across different types of R&D. It offers a quantification of the fact that R&D aimed at improving existing products has a significantly higher ratio of social to private return than R&D aimed at creative destruction, due to a small inferred quality improvement associated with creative destruction.

The remainder of this chapter is structured as follows. In Section 2.2, I develop a model of endogenous growth through own-product innovation and creative destruction which incorporates within-industry employee spinouts and noncompete agreements.

Section 2.3 describes the quantification of the model. In Section 2.4, I present the policy counterfactuals. Section 2.5 concludes.

2.2 Model

In this section I develop a model of endogenous growth with R&D-induced spinouts and noncompete agreements. It extends a standard quality ladders model of endogenous growth through own-product innovation and creative destruction, drawing mostly from Grossman and Helpman 1991, Acemoglu and Cao 2015, and Akcigit and Kerr 2018. The new features are that own-product R&D induces spinout formation and that incumbents can use noncompetes to shut down this channel.

2.2.1 Representative household

I model a continuous time economy, starting at $t = 0$. The representative household has CRRA preferences over consumption streams of the final good $\{C(t)\}_{t \geq 0}$, given by

$$U(\{C(t)\}_{t \geq 0}) = \int_0^\infty e^{-\rho t} \frac{C(t)^{1-\theta} - 1}{1-\theta} dt. \quad (2.1)$$

In each period $t \geq 0$, the household is endowed with $\bar{L}_{RD} \in (0, 1)$ units of R&D labor as well as $1 - \bar{L}_{RD}$ units of production labor which is used in the production of

intermediate and final goods. The labor resource constraints are

$$L_{RD} \leq \bar{L}_{RD}, \quad (2.2)$$

$$L_P \leq 1 - \bar{L}_{RD}. \quad (2.3)$$

The household takes as given profits it receives from the ownership of all firms in the economy. The household also has access to an instantaneous risk-free bond that exists in zero net supply. Note that the above specification implies that the supply of R&D labor is inelastic.⁷ This implies that productivity growth is determined entirely by the relative allocation of R&D labor between firms.

In reality, of course, the aggregate allocation of labor to R&D also matters, and it is endogenous. Factors affecting the demand for R&D labor, such as the enforcement of NCAs considered in this paper, affect the allocation of labor between production and R&D. The present model can be viewed as an approximation that is more accurate in the medium term, when the endogenous response of aggregate R&D labor supply is constrained by the slow process of human capital accumulation. Alternatively, it can be interpreted as a stylized model which highlights the effects of R&D incentives on the allocation of R&D labor.

2.2.2 Final goods producer

The final good is produced competitively using production labor and a continuum of intermediate goods $j \in [0, 1]$ which, at any given time t , exist in a finite set of $I_{jt} \geq 1$

⁷As noted in the introduction, this increases tractability significantly by ensuring that the flow of corporate profits depends only on the level of production technology.

qualities $\{q_{jti}\}_{0 \leq i \leq I_{jt}}$. The production $Y(t)$ of the final good is given by

$$Y(t) = F(L_{Ft}, \{q_{jti}\}, \{k_{jti}\}) = \frac{L_{Ft}^\beta}{1-\beta} \int_0^1 \left(\sum_{i=0}^{I_{jt}} q_{jti}^{\frac{\beta}{1-\beta}} k_{jti} \right)^{1-\beta} dj, \quad (2.4)$$

where $k_{jti} \geq 0$ is the quantity used of intermediate good j of quality q_{jti} . This specification implies that different qualities of good j are perfect substitutes. The use of a CES aggregator for intermediate goods with an elasticity that is different from one (i.e., Cobb-Douglas) simplifies the analysis by allowing me to abstract from limit pricing using a simple microfoundation taken from Akcigit and Kerr 2018. The exponent $\frac{\beta}{1-\beta}$ on q_{jti} and later specification of the intermediate goods production and innovation technology together yield balanced growth. The model could be specified with $q_{jti}k_{jti}$ as the summand instead, a setting which can be interpreted as cost saving innovations. In that case, however, balanced growth requires a similar exponent in the production and innovation technology for intermediate goods. The present specification follows Akcigit and Kerr 2018. Several alternatives are discussed in Acemoglu 2009.

Define $\bar{q}_{jt} = \max_{0 \leq i \leq I_{jt}} \{q_{jti}\}$ as the *frontier* quality of good j . In equilibrium, the final goods production function admits a simpler representation

$$Y(t) = F(L_{Ft}, \{\bar{q}_{jt}\}, \{\bar{k}_{jt}\}) = \frac{L_{Ft}^\beta}{1-\beta} \int_0^1 \bar{q}_{jt}^\beta \bar{k}_{jt}^{1-\beta} dj. \quad (2.5)$$

There is no storage technology for the final good and its price is normalized to 1 in every period.

2.2.3 Intermediate goods production and innovation

Incumbents

Each quality q_{jti} of each good j is produced by a firm which has a monopoly on production of that quality of good j . Intermediate goods j of any quality are produced according to the production function

$$k_{jti} = H(\ell_{jti}; Q) = Q\ell_{jti}, \quad (2.6)$$

where $\ell_{jti} \geq 0$ is the labor input and $Q_t = \int_0^1 \bar{q}_{jt} dj$ is the average frontier quality level in the economy. The producer which produces the frontier quality of good j is denoted *incumbent* j . There is no storage of intermediate goods.

As alluded above, the scaling with average quality Q_t is necessary for a balanced growth path (BGP) in this setting. It implies that improvements in the quality of good j increases the productivity of all other goods $j' \neq j$ through a knowledge spillover externality. In this case, balanced growth requires the scaling to be linear in order to offset the fact that the production wage increases linearly with average quality Q_t .

Intermediate goods market structure The following setup, which enables me to abstract from limit pricing, is drawn from Akcigit and Kerr 2018. Within each good j , intermediate goods producers play a two-stage Bertrand competition game at each time $t \geq 0$. In the first stage, participants bear a cost of $\varepsilon > 0$ units of the final good in exchange for a right to compete in the second stage. Then, in the second

stage, they engage in Bertrand competition against each other and against producers of goods $j' \neq j$. Optimal pricing under Bertrand competition in the second stage implies that all producers not on the frontier will have zero profits. By backward induction, such producers do not pay the ε entry cost. The incumbent therefore has a second-stage monopoly over good j which implies the optimal price is the monopolistic competition markup $(1 - \beta)^{-1}$ over marginal costs. I study the limit of this model as $\varepsilon \rightarrow 0$.

Own-product innovation Incumbent j can hire R&D labor to improve the quality of the good she can produce. I refer to this as *own-product innovation* or OI, following Garcia-Macia et al. 2019 and Klenow and Li 2020. By performing a flow of z_{jt} units of R&D, she receives a Poisson intensity of χz_{jt} of innovating on good j , where $\chi > 0$ is an exogenous parameter representing the incumbent's R&D productivity. This implies an arrival rate of incumbent innovations of

$$\tau_{jt} = \chi z_{jt}. \quad (2.7)$$

A successful own-product innovation improves the quality of the incumbent's product by an exogenous *step size* $\lambda > 1$. Note that incumbent R&D exhibits constant returns to scale. This is necessary to have a closed form solution.⁸

I make a standard scaling assumption that applies to all forms of R&D. Specifically, the flow labor cost of z_{jt} units of R&D directed at a product of quality $\bar{q}_{jt}$ is given by $\frac{\bar{q}_{jt}}{Q_t} z_{jt}$. This captures the idea that higher quality products require more human

⁸In Appendix 2.D.1 I show that the main result is quantitatively similar when considering a model where incumbents have decreasing returns to scale.

capital to improve. It also implies that there are knowledge spillovers in R&D, as an increase in the quality of good j improves the R&D technology of all other goods $j' \neq j$. An assumption of this kind is also necessary for the existence of a balanced growth path. The proportionality with $\bar{q}_{jt}$ balances the same scaling in the reward to innovation, ensuring that the return on R&D is constant across goods j . The inverse proportionality with Q_t ensures that the average firm is always equally productive at proportional innovations.⁹

I assume that only incumbents can perform own-product R&D. That is, when an incumbent is overtaken by an entrant or spinout innovation (described in the next section), she loses access to the OI R&D technology and therefore cannot use it to “catch up” to the frontier. One interpretation is that learning by doing means the current producer of a product has unique insights into how to improve on it. This assumption significantly increases tractability.¹⁰

Spinouts and noncompete agreements

A flow of R&D spending on own-product innovation induces a positive probability of being overtaken by an employee spinout unless the incumbent imposes a noncompete on R&D labor. The decision of whether a noncompete is used is made instant-by-

⁹The cost of R&D could be assumed to scale up faster than $\bar{q}_{jt}$, which would imply that higher quality products grow slower. In the current setup this would preclude a BGP because there is no stationary distribution of product quality. Adding a fixed labor cost and imitative entry would lead to a stationary distribution by inducing a lower exit barrier. For a related discussion, see Gabaix 2009 and Acemoglu and Cao 2015.

¹⁰Without this assumption, the incumbent problem would have an additional state variable (since falling away from the frontier is no longer an absorbing state) and an additional distribution would need to be tracked (the number of incumbents with the technology to produce each infra-frontier good j).

instant and prevents spinouts during the time it is used. To be precise, I assume that if incumbent j conducts z_{jt} units of R&D effort, she faces a Poisson intensity of spawning a spinout given by

$$\tau_{jt}^S = (1 - \mathbb{1}_{jt}^{NCA})\nu z_{jt}, \quad (2.8)$$

where $\mathbb{1}_{jt}^{NCA} = 1$ if and only if an NCA is used in that instant. The contract is renegotiated instant-by-instant in the sense that the employee takes as given the incumbent's NCA policy and wage offered when deciding whether to supply R&D in each instant. Therefore, the incumbent cannot use an NCA without potentially having to offer a higher wage to compensate the employee for the fact that he will not be able to profit from WSO formation.

Upon paying an entry cost, which I discuss in the next paragraph, a spinout from incumbent j of quality $\bar{q}_{jt}$ is able to produce good j with quality $\lambda\bar{q}_{jt}$, and it immediately becomes the new incumbent. Due to the no catch-up assumption, the previous incumbent's profits go to zero forever after. The exogenous parameter $\nu \geq 0$ encodes the rate at which R&D increases the likelihood of replacement by a WSO. Recall that z_{jt} applied to a good of relative quality $\frac{q}{Q_t}$ requires $\frac{q}{Q_t}z_{jt}$ units of R&D labor. Therefore, this specification implies that the rate of spinout generation of a unit of R&D labor is inversely proportional to the relative quality $\frac{q}{Q_t}$ of the good upon which it seeks to innovate. This is consistent with the scaling assumptions made previously about the labor cost of R&D.

In order to enter, employee spinouts must pay an entry cost of $\kappa_e V(j, t | \lambda\bar{q}_{jt})$ units of the final good in order to begin producing, where $\kappa_e \in [0, 1)$ is exogenous and

$V(j, t|\lambda\bar{q}_{jt})$ denotes the equilibrium private value of incumbent j at time t with quality $\lambda\bar{q}_{jt}$. This cost represents non-R&D expenditures required by creative destruction innovation but not by own-product innovation, such as marketing costs or the costs of setting up a new firm.¹¹ The scaling of the cost with $V(j, t|\lambda q_{jt})$ is natural as it simply means that the cost of entry is proportional to the value of the incumbency position obtained through entry. Further, this scaling assumption allows for an analytical solution to the model.

Incumbents also have to pay a cost in order to use an NCA. Specifically, when incumbent j imposes an NCA on z_j units of R&D, she must pay a flow cost $\kappa_c \nu V(j, t|\bar{q}_j) z_j$ units of the final good. Given (2.8), incumbent j overall pays

$$\text{NCA cost}_{jt} = \tau_{jt}^S \kappa_c V(j, t|q). \quad (2.9)$$

The NCA enforcement cost reflects the direct cost using an NCA. Even if there are no technical restrictions on what kinds of NCAs are valid, determining competition between businesses may be expensive. Moreover, many jurisdictions do, in fact, impose such restrictions, and resources can be invested to prove that the conditions of those restrictions do not apply. Overall, it seems plausible that investing resources increases the likelihood of a successful enforcement of an NCA. Note also that a value of $\kappa_c = \infty$ can be interpreted as ban on the use of NCAs and a value $\kappa_c = 0$ can be interpreted as a complete relaxation of barriers to the use of NCAs.

¹¹On the other hand, these expenditures could also take the form of transfers of rent to other early employees or financiers. In this interpretation, entry by spinouts – and creative destruction in general – is relatively more socially valuable. Hence, the choice of interpretation does have implications for welfare analysis. I proceed assuming that they are real costs and consider the transfers interpretation in robustness checks, where I find similar results.

As with the entry cost, the factor $V(j, t|q)$ implies that the cost of enforcing NCAs is proportional to the equilibrium value of the incumbent firm. The economic justification is that valuable incumbency positions require more resources to protect via NCAs. In the context of the model, this specification means that the cost of enforcing an NCA on a given unit of R&D labor is proportional to both the value of the WSOs that labor will generate in the absence of an NCA, and the expected loss of incumbent value from an absence of NCAs. As with the entry cost, this assumption also improves model tractability by simplifying the analysis of the optimal noncompete policy (see Section 2.2.5).

Finally, it is important to note that I have assumed that spinout entry does not directly reduce the rate at which incumbent R&D results in successful OI. Instead, spinouts enter when an additional, independent Poisson process with arrival rate νz_j has an arrival. The interpretation is that spinouts in this model do not embody stolen ideas that otherwise would have been implemented by the parent firm. Rather, R&D labor generates *additional* innovations which the employee can use to offer a higher quality product than the incumbent firm. This is consistent with the finding in Klepper 2007 that spinouts often occur when the employee finds the idea more valuable than his employer rather than through idea stealing. It is important to note that this assumption has important consequences for the private and social usefulness of NCAs. In particular, to the extent that spinouts take ideas that otherwise would be implemented inside the firm, they are less valuable both privately and socially.

In the context of this model and calibration, the socially beneficial effects of NCA enforcement would be larger.¹²

Entrants

In addition to own-product innovation and spinout formation, growth also results from creative destruction by entrant firms. Specifically, for each frontier quality good j there is a unit mass of entrants indexed by $e \in [0, 1]$.¹³ By performing a flow of $\hat{z}_{jet}$ units of R&D, an entrant receives a Poisson intensity of $\hat{z}_{jet}\hat{\chi}\hat{z}_{jt}^{-\psi}$ of innovating on good j , where $\bar{\hat{z}}_{jt} = \int_0^1 \hat{z}_{jet} de$ total entrant R&D dedicated improving good j . From now I drop the bar notation when it is clear from context. Because each entrant is infinitesimal, their R&D efforts have constant returns to scale at the individual level. Note that this means entrant optimization will only pins down $\hat{z}_{jt}$ in equilibrium; as this does not affect aggregates, I will assume that $\hat{z}_{jet} = \hat{z}_{jt}$. Aggregating over $e \in [0, 1]$, the arrival rate of entrant innovations on good j is

$$\hat{\tau}_{jt} = \hat{\chi}\hat{z}_{jt}^{1-\psi}. \quad (2.10)$$

As with the other forms of innovation, the cost in terms of R&D labor is proportional to the relative quality of the good $\frac{\bar{q}_{jt}}{Q_t}$ and a successful innovation yields a monopoly on the production of good j with quality $\lambda\bar{q}_{jt}$.

¹²The validity of this assumption could be tested empirically with sufficiently exogenous variation in the enforceability of NCAs or in the use of NCAs. One could study, for example, whether R&D generates fewer patents when R&D managers and employees are not bound by NCAs. However, as noted in the introduction, interpreting the results of such regressions requires care to control for the endogeneity of firm and employee selection into enforcement regimes and contracts.

¹³As is standard in this type of model, I assume for simplicity that entrants innovate only on frontier quality goods.

The parameter $\psi > 0$ introduces decreasing returns at the level of good j . It represents a *congestion* externality in the entrant innovation technology. This is similar to the congestion externality present in search and matching models. Intuitively, due to a lack coordination, entrants attempt similar approaches to solve the same problem. This duplication of effort reduces the overall returns to entrant R&D when considered at the level of good j .

Finally, as with spinouts, entrants must also pay an entry cost of $\kappa_e V(j, t | \lambda \bar{q}_{jt})$ in units of the final good in order to enter once they have successfully innovated on a good of quality $\bar{q}_{jt}$. The interpretation is the same as with spinouts as both types of firms are engaging in creative destruction and not own-product innovation.

2.2.4 Competitive financial intermediary

The representative household owns a competitive financial intermediary which in turn owns all firms in the economy and remits their profits back to the representative household. Individual firms in the economy maximize profits subject to the household's risk-free discount rate (i.e., there is no collusion due to common ownership). When the representative household receives a shock in good j that allows it to form a spinout, it sells the spinout to the financial intermediary at full private value (i.e. discounting the spinouts profits at the same risk-free discount rate). The financial intermediary takes the entry of the spinout as given, and therefore is willing to pay this value even though the entry of the spinout reduces the value of an existing incumbent.¹⁴

¹⁴The purpose of this construction is to avoid having to assume that the representative household does not take into account the loss of value of the incumbents due creative destruction by its own spinouts.

2.2.5 Equilibrium

Definition of equilibrium

The model involves idiosyncratic risk for each good j . In each realization of a given equilibrium, the price at time t of the frontier intermediate good j , the R&D wage paid by incumbent j , and the allocation of production and R&D labor to the frontier intermediate good j all depend on the stochastic realization of the frontier quality stochastic process $\bar{q}_{jt}$. To study this kind of equilibrium, I look for an equilibrium where prices and quantities are deterministic functions of $(j, t|\bar{q}_{jt})$. I also use q to refer to $\bar{q}_{jt}$ (that is, equilibrium objects are written as functions of $(j, t|q)$) when the meaning is clear from context. This approach follows Acemoglu 2009.

Definition 1. An *equilibrium* of this model consists of household consumption $C(t)$ and bond holdings $A(t)$; final good production $Y(t)$; frontier intermediate goods prices $p(j, t|q)$ and quantities $k(j, t|q)$; production wages $\bar{w}(t)$ and production labor allocation to final goods $L_F(t)$ and intermediate goods $\ell_I(j, t|q)$; R&D wages paid by entrants $\hat{w}_{RD}(t)$, by incumbents using and not using noncompetes $w_{RD}(j, t|q, \mathbf{1}^{NCA})$; R&D labor allocations across incumbents $\ell_{RD}(j, t|q)$ and across entrants $\hat{\ell}_{RD}(j, t|q)$; and noncompete contract allocations $\mathbf{1}^{NCA}(j, t|q)$ such that

1. The final goods firm maximizes profits.
2. Each incumbent j optimally chooses production, R&D labor demand, and the use of NCAs.
3. Entrants optimize their R&D labor demand.

4. The representative household optimizes production and R&D labor supply, consumption and savings.
5. The competitive financial intermediary maximizes the discounted present value of profits remitted to the household.
6. Markets clear (final goods, risk-free bonds in zero net supply).

For the sake of tractability, I will restrict attention to symmetric balanced growth path equilibria. This requires two more definitions.

Definition 2. A *balanced growth path equilibrium* (BGP) is an equilibrium where there exist $g, C_0, Q_0 > 0$ such that

$$C(t) = C_0 e^{gt}, \quad (2.11)$$

$$Q_t = Q_0 e^{gt}. \quad (2.12)$$

Definition 3. A *symmetric balanced growth path equilibrium* (symmetric BGP) is a BGP where $z_{jt} = z$ and $\hat{z}_{jet} = \hat{z}$ for all $j, e \in [0, 1], t \geq 0$.

Symmetric BGPs are a natural type of equilibrium given the symmetric setup of the model. It is the typical case studied, e.g. in Grossman and Helpman 1991 and Acemoglu and Cao 2015.¹⁵

¹⁵One could relax the assumption that $z_{jt} = z$ as long as $\int_0^1 z_{jt} \frac{\bar{q}_{jt}}{Q_t} dj$ is constant on the BGP. For a discussion of this, Acemoglu 2009.

Static equilibrium

The first step is to characterize the static equilibrium given a profile of frontier qualities $\{\bar{q}_j\}$. Note that I have omitted the dependence on t for the sake of clarity. In addition, since only the frontier quality is produced in equilibrium, in this section I will drop the $\bar{q}_j$ notation and refer to the frontier good's quality and quantity by q_j and k_j , respectively. The following definition abuses notation slightly as it reuses some of the symbols in the definition of equilibrium.

Definition 4. Given a profile a frontier qualities $\{q_j\}$, a *static equilibrium* consists of frontier intermediate goods prices p_j and quantities k_j , production wages $\bar{w}$, and a production labor allocation to final goods L_F and intermediate goods ℓ_j such that

1. The final goods firm chooses its demand for production labor and intermediate goods in order to maximize profits.
2. Intermediate goods firms choose their demand for production labor in order to maximize profits.

Given this definition, one can directly compute the unique static equilibrium of the model given any profile of qualities. su

Proposition 2.2.1. *Given a profile of frontier qualities $\{q_j\}$, there exists a unique static equilibrium.*

Proof. Final goods producer optimization implies the inverse demand function for intermediate goods

$$p_j = L_F^\beta q_j^\beta k_j^{-\beta}. \quad (2.13)$$

The intermediate goods market structure implies that incumbent j can effectively ignore lower quality producers of good j when making pricing decisions. She therefore sets k_j to solve

$$\pi(q_j) = \max_{k_j \geq 0} \left\{ L_F q_j^\beta k_j^{1-\beta} - \frac{\bar{w}}{Q} k_j \right\}, \quad (2.14)$$

where $\bar{w}$ is the equilibrium production goods wage and $Q = \int_0^1 q_j dj$ is average frontier good quality. The solution to this maximization problem yields expressions for intermediate goods pricing, production labor demand, and production, given by

$$k_j = \left[\frac{(1-\beta)Q}{\bar{w}} \right]^{1/\beta} L_F q_j, \quad (2.15)$$

$$\ell_j = k_j/Q, \quad (2.16)$$

$$p_j = \frac{\bar{w}}{(1-\beta)Q}. \quad (2.17)$$

Substituting (2.15) into the first-order condition for final goods firm optimal production labor demand yields an expression for the equilibrium wage $\bar{w}$, given by

$$\bar{w} = \tilde{\beta}Q, \quad (2.18)$$

$$\tilde{\beta} = \beta^\beta (1-\beta)^{1-2\beta}. \quad (2.19)$$

Substituting (2.15) and (2.18) into the expression for profit in (2.14) yields

$$\pi_j = \overbrace{(1-\beta)\tilde{\beta}L_F}^{\tilde{\pi}} q_j. \quad (2.20)$$

Substituting (2.15) into (2.16) and integrating $L_I = \int_0^1 \ell_j dj$ yields aggregate labor allocated to intermediate goods production

$$L_I = \left(\frac{1 - \beta}{\tilde{\beta}} \right)^{1/\beta} L_F. \quad (2.21)$$

Using (2.21) and $L_I + L_F = L_P$ in the labor resource constraint (2.3) yields

$$L_F = \frac{1 - \bar{L}_{RD}}{1 + \left(\frac{1 - \beta}{\tilde{\beta}} \right)^{1/\beta}}. \quad (2.22)$$

Output can be computed by substituting (2.15) into (2.5), yielding

$$Y = \frac{(1 - \beta)^{1-2\beta}}{\beta^{1-\beta}} Q L_F. \quad (2.23)$$

□

Existence and uniqueness of symmetric BGP

The static equilibrium derived in the previous section implies, for each profile of qualities $\{\bar{q}_{jt}\}$, a level of final goods production $Y(t)$, allocations of production labor, intermediate goods prices, and an allocation of intermediate goods. Moreover, it also implies that the flow of profits to incumbent j of quality q is given by $\pi(j, t|q) = \tilde{\pi}q$, which in turn dictates the dividends the household receives from the financial intermediary. All that remains to characterize the set of symmetric BGPs is to find R&D wages and labor allocations, consumption, and financial asset holdings that are consistent with household, incumbent, and entrant optimization.

Household optimization I begin by deriving the equilibrium conditions that arise from the representative household's optimization problem. As noted in the definition of equilibrium, the household takes as given incumbent R&D wages and NCA policies $w_{RD}(j, t|q, \mathbb{1}^{NCA})$, $\mathbb{1}^{NCA}(j, t|q)$, entrant R&D wages $\hat{w}_{RD}(t)$, production wages $\bar{w}(t)$, interest rates $\{r_t\}$, and profits from the financial intermediary $\{\Pi_t\}$. To simplify notation, I use the subscript jt to denote a particular realization of an equilibrium object. Specifically, I use $\mathbb{1}_{jt}^{NCA}$ to denote $\mathbb{1}^{NCA}(j, t|\bar{q}_{jt})$, $\ell_{RD,jt}$ to denote $\ell_{RD}(j, t|\bar{q}_{jt}, \mathbb{1}^{NCA}(j, t|\bar{q}_{jt}))$, $\hat{\ell}_{RD,jt}$ to denote $\hat{\ell}_{RD}(j, t|\bar{q}_{jt})$, and $w_{RD,jt}$ to denote $w_{RD}(j, t|\bar{q}_{jt}, \mathbb{1}_{jt}^{NCA})$. I also use t subscripts to denote production wages and the interest rate. Given this, the representative household solves

$$\begin{aligned} & \begin{aligned} & \text{maximize} \\ & \{C(t)\}_{t \geq 0} \\ & \{A(t)\}_{t \geq 0} \\ & \{L_P(t)\}_{t \geq 0} \\ & \{\ell_{RD}(j, t|q, \mathbb{1}^{NCA})\}_{j \in [0, 1], t \geq 0} \\ & \{\hat{\ell}_{RD}(j, t|q)\}_{j \in [0, 1], t \geq 0} \end{aligned} & \int_0^\infty e^{-\rho t} \frac{C(t)^{1-\theta} - 1}{1-\theta} dt \end{aligned} \quad (2.24a)$$

subject to

$$\begin{aligned} \dot{A}(t) &= -C(t) + r_t A(t) + \Pi_t + \bar{w}_t L_P(t) \quad (\text{Financial wealth law of motion}) \\ &+ \int_0^1 \hat{w}_{RD}(t) \hat{\ell}_{RD,jt} dj + \int_0^1 w_{RD,jt} \ell_{RD,jt} dj \\ &+ \int_0^1 (1 - \mathbb{1}_{jt}^{NCA}) \nu\left(\frac{\bar{q}_{jt}}{Q_t}\right)^{-1} \ell_{RD,jt} (1 - \kappa_e) V(j, t|\lambda \bar{q}_{jt}) dj, \end{aligned}$$

$$A(0) = 0, \quad (\text{Initial wealth})$$

$$\lim_{t \rightarrow \infty} e^{-\int_0^t r_s ds} A(t) \geq 0, \quad (\text{No Ponzi-game})$$

$$\int_0^1 (\ell_{RD,jt} + \hat{\ell}_{RD,jt}) dj \leq \bar{L}_{RD}, \quad (\text{R\&D labor endowment})$$

$$L_P(t) \leq 1 - \bar{L}_{RD}. \quad (\text{Production labor endowment})$$

There are also non-negativity constraints on consumption and labor supply. Thus, the household consumes out of profits remitted by the intermediary Π_t , returns from holdings of the risk free bond $r_t A(t)$, wages earned from production labor supply $\bar{w}_t L(t)$, wages earned from R&D labor supply $\int_0^1 (w_{RD,jt} \ell_{RD,j}(t) + \hat{w}_{RD,t} \hat{\ell}_{RD,j}(t)) dj$, and earnings from sales of spinouts to the financial intermediary $\int_0^1 (1 - \mathbb{1}_{jt}^{NCA}) (\frac{\bar{q}_{jt}}{Q_t})^{-1} \nu (1 - \kappa_e) V(j, t | \lambda \bar{q}_{jt}) \ell_{RD,j}(t) dj$.

Because the household's expected payoff from working at a given incumbent j depends not only on the wage but also on the expected present value of spinouts formed producing good j , it is necessary to explicitly model the household's R&D labor allocation for each individual good j as a function of the frontier quality realization $\bar{q}_{jt}$. While this is not strictly necessary for R&D labor supplied to entrants, I present the problem symmetrically.

The expression for the value of earnings from sales of spinouts follows because a spinout occurs in good j with Poisson intensity $(1 - \mathbb{1}_{jt}^{NCA}) (\frac{\bar{q}_{jt}}{Q_t})^{-1} \nu \ell_{RD,j}(t)$ and is sold to the financial intermediary at the price of $(1 - \kappa_e) V(j, t | \lambda \bar{q}_{jt})$.¹⁶

Lemma 2.2.1. *In a symmetric BGP with $z > 0$, R&D wages satisfy*

$$\hat{w}_{RD}(t) \leq w_{RD}(j, t | \bar{q}_{jt}) + (1 - \mathbb{1}_{jt}^{NCA})(j, t | \bar{q}_{jt}) \left(\frac{\bar{q}_{jt}}{Q_t} \right)^{-1} \nu (1 - \kappa_e) V(j, t | \lambda \bar{q}_{jt}) \quad (2.25)$$

for all $t \geq 0$ and $j \in [0, 1]$. If $\hat{z} > 0$, (2.25) holds with equality.

¹⁶To be more precise, the household forms, and sells, a spinout in each good j upon the arrival of an independent Poisson process N_{jt} with time-varying hazard rate $(1 - \mathbb{1}_{jt}^{NCA}) \nu (\frac{\bar{q}_{jt}}{Q_t})^{-1} \ell_{RD,jt}$. The expected payoff of spinouts from good j is therefore $(1 - \mathbb{1}_{jt}^{NCA}) \nu (\frac{\bar{q}_{jt}}{Q_t})^{-1} \ell_{RD,jt} (1 - \kappa_e) V(j, t | \lambda \bar{q}_{jt}) dj dt$. The budget constraint integrates over $j \in [0, 1]$ and, heuristically, divides by dt .

Proof. Optimality dictates that the household supplies R&D labor only to jobs which provide the highest compensation. Therefore, in order to be consistent with household optimal labor supply when $z > 0$, (2.25) must hold for all $t \geq 0$ and $j \in [0, 1]$. If, in addition $\hat{z} > 0$, the household must be indifferent between supplying R&D to incumbents and entrants and (2.25) must therefore hold with equality. $\square$

Intuitively, in a symmetric BGP, the expected compensation received from each incumbent in exchange for a given amount of R&D labor must be constant. Next, optimal savings gives rise to a standard Euler equation which holds in equilibrium for all $t \geq 0$, given by

$$\frac{\dot{C}(t)}{C(t)} = \frac{1}{\theta}(r_t - \rho). \quad (2.26)$$

Lemma 2.2.2. *In a symmetric BGP, $r_t = r$.*

Proof. In a symmetric BGP, $\frac{\dot{C}(t)}{C(t)} = g$ is constant. By (2.26), $r_t = \theta g + \rho =: r$. $\square$

Finally, there is a transversality condition on financial wealth. In this model it holds trivially, as $A(t) = 0$ in equilibrium. Therefore I omit it from the exposition. The typical transversality condition, which would be imposed here if the household traded claims on the competitive financial intermediary, manifests later in a necessary and sufficient condition for finiteness of household utility.

Entrant optimization I briefly consider the optimization problem of entrants in order to prove a result which is useful later. Entrant e in good j chooses $\hat{z}_{jet}$ to maximize profits, taking as given prices (i.e. the R&D wage, the interest rate), good

j entrant R&D $\hat{z}_{jt}$, and the value of being an incumbent in good j at time t with quality $\lambda\bar{q}_{jt}$, denoted $V(j, t|\lambda\bar{q}_{jt})$. The resulting optimization problem is

$$\max_{\hat{z}_{jet} \geq 0} \overbrace{\hat{\chi}^{\hat{z}_{jet} \hat{z}_{jt}^{-\psi}} (1 - \kappa_e) V(j, t|\lambda\bar{q}_{jt})}^{\text{Innovation rate}} - \underbrace{\hat{z}_{jet} \frac{\bar{q}_{jt}}{Q_t} \hat{w}_{RD}(t)}_{\substack{\text{Cost of R\&D} \\ \text{R\&D labor}}} . \quad (2.27)$$

$\underbrace{\hspace{10em}}_{\mathbb{E}[\text{Payoff from innovation}]}$

Lemma 2.2.3. *In any equilibrium, $\hat{z}_{jt} > 0$. In a symmetric BGP, $\hat{z} > 0$.*

Proof. The first order condition corresponding to (2.27) is given by

$$\hat{\chi}^{\hat{z}_{jt}^{-\psi}} (1 - \kappa_e) V(j, t|\lambda\bar{q}_{jt}) \leq \frac{\bar{q}_{jt}}{Q_t} \hat{w}_{RD}(t), \quad (2.28)$$

with equality if $\hat{z}_{jt} > 0$. Because $\kappa_e < 1$, the left-hand side goes to $+\infty$ as $\hat{z}_{jt} \rightarrow 0$ while the right-hand side remains constant. Therefore, this condition can only hold if $\hat{z}_{jt} > 0$. As $\forall j \in [0, 1]$, $\hat{z}_{jt} = \hat{z}$ in a symmetric BGP, this implies $\hat{z} > 0$. $\square$

Incumbent optimization Next, I turn to equilibrium conditions stemming from incumbent and entrant optimization. Incumbent j takes as given flow profits $\pi(j, t|q) = \tilde{\pi}q$ derived from the static equilibrium, the interest rate r_t , which she uses to discount future profits, the rate of creative destruction by entrants $\hat{\tau}(j, t|q)$, as well as the R&D wage she must pay conditional on her choice of NCA policy $w_{RD}(j, t|q, \mathbb{1}^{NCA})$. The discounting is at the risk-free rate r_t because the financial intermediary diversifies across incumbents and there is no aggregate uncertainty.

On the equilibrium path, Lemma 2.2.1 gives an expression for the value of the incumbent R&D wage. However, to define the optimal NCA policy of the incumbent,

it is necessary to specify the incumbent R&D wage conditional on any choice of NCA policy. Because the R&D labor market is competitive, the incumbent takes as given that she can hire as much R&D labor as necessary provided that she offers total compensation equal to that offered by entrants. If she does not use an NCA, this compensation includes the expected value of spinouts formed by the household.

Lemma 2.2.4. *In a symmetric BGP, the incumbent maximizes profits taking as given*

$$w_{RD}(j, t|q, \mathbb{1}^{NCA}) + (1 - \mathbb{1}^{NCA})\left(\frac{q}{Q_t}\right)^{-1}\nu(1 - \kappa_e)V(j, t|\lambda q) = \hat{w}_{RD}(t), \quad (2.29)$$

Proof. By the same argument as in Lemma 2.2.1, the expression on the left of the equals sign is the expected flow compensation to a unit of R&D labor required to attract any workers. The expression on the right is the equilibrium price of R&D labor. Lemma 2.2.1 already yields the result for the equilibrium choice of $\mathbb{1}^{NCA}$. The off-equilibrium wage is simply that wage that would be required to actually hire R&D labor in the equilibrium that obtains using the off-equilibrium choice of NCA policy. This is also equal to the equilibrium price of R&D labor $\hat{w}_{RD}(t)$. $\square$

The above discussion implies that the value of an incumbent $V(j, t|q)$ must satisfy a Hamilton-Jacobi-Bellman equation,

$$\begin{aligned}
& \overbrace{(r_t + \hat{\tau})}^{\text{Creative destruction}} V(j, t|q) - \dot{V}(j, t|q) = \overbrace{\tilde{\pi}q}^{\text{Flow profits}} + \max_{\substack{\mathbb{1}^{NCA} \in \{0,1\} \\ z \geq 0}} \left\{ z \left[\overbrace{\chi(V(j, t|\lambda q) - V(j, t|q))}^{\mathbb{E}[\text{Payoff from own-innovation}]} \right. \right. \\
& \quad - \underbrace{\left(\frac{q}{Q_t} \right)}_{\text{scaling of R\&D cost}} \left(\underbrace{w_{RD,jt}(\mathbb{1}^{NCA})}_{\text{R\&D wage depends on NCA}} + \underbrace{\left(\frac{q}{Q_t} \right)^{-1}}_{\text{scaling of spinout formation rate}} \overbrace{(1 - \mathbb{1}^{NCA})\nu V(j, t|q)}^{\mathbb{E}[\text{Loss from spinout CD}]} \right. \\
& \quad \left. \left. + \underbrace{\left(\frac{q}{Q_t} \right)^{-1}}_{\text{scaling of NCA cost}} \overbrace{\mathbb{1}^{NCA} \kappa_c \nu V(j, t|q)}^{\text{NCA cost}} \right) \right] \Bigg\}, \tag{2.30}
\end{aligned}$$

where $\tilde{\pi}$ is defined in (2.20).

The first proposition shows that, in a symmetric BGP, the value function must have a linear form.

Proposition 2.2.2. *In a symmetric BGP, the value function of the incumbent is given by*

$$V(j, t|q) = \tilde{V}q, \tag{2.31}$$

for some $\tilde{V} > 0$.

Proof. Appendix 2.B.1. □

The above Proposition implies the following two corollaries.

Corollary 2.2.1. *In a symmetric BGP, there exist $\tilde{w}_{RD}, \tilde{w}_{RD} > 0$ such that*

$$\hat{w}_{RD}(t) = \tilde{w}_{RD} Q_t, \quad (2.32)$$

$$w_{RD}(j, t|q, \mathbb{1}^{NCA}) = \tilde{w}_{RD}(\mathbb{1}^{NCA}) Q_t. \quad (2.33)$$

Proof. Dividing the entrant first-order condition by $\bar{q}_{jt}$ yields

$$\hat{\chi} \hat{z}^{-\psi} \tilde{V} \lambda = \frac{\hat{w}_{RD}(t)}{Q_t}, \quad (2.34)$$

implying that $\frac{\hat{w}_{RD}(t)}{Q_t}$ must be constant, i.e. $\hat{w}_{RD}(t) = \tilde{w}_{RD} Q_t$ for some $\tilde{w}_{RD}$. Using this and $V(j, t|q) = \tilde{V} q$ in Lemma 2.2.4 yields $w_{RD}(j, t|q, \mathbb{1}^{NCA}) = \tilde{w}_{RD}(\mathbb{1}^{NCA}) Q_t$. $\square$

From now on, I drop the $\sim$ superscript when referring to $\tilde{w}_{RD}$ and $\tilde{w}_{RD}$ and the meaning is clear from context. The next proposition characterizes the equilibrium NCA policy of all incumbents in a symmetric BGP with $z > 0$.

Proposition 2.2.3. *In a symmetric BGP with $z > 0$, the equilibrium NCA policy of all incumbents is given by*

$$\mathbb{1}_{jt}^{NCA} = \mathbb{1}^{NCA} = \begin{cases} 1 & \text{if } \kappa_c < \bar{\kappa}_c, \\ 0 & \text{if } \kappa_c > \bar{\kappa}_c, \\ \{0, 1\} & \text{if } \kappa_c = \bar{\kappa}_c, \end{cases} \quad (2.35)$$

where $\bar{\kappa}_c = 1 - (1 - \kappa_e)\lambda$.

Proof. Appendix 2.B.1. $\square$

Proposition 2.2.3 implies that, in a symmetric BGP, all incumbents choose the same NCA policy, except on the knife-edge $\kappa_c = \bar{\kappa}_c$ where incumbents are indifferent between $\mathbb{1}^{NCA} = 0$ and $\mathbb{1}^{NCA} = 1$. This results from the fact that the only heterogeneity between incumbents in a symmetric BGP is their quality, which does not affect the optimal policy. The model could be extended in various ways so that some firms do and some firms do not use NCAs, at the expense of requiring a numerical solution.¹⁷

The proof of Proposition 2.2.3 follows from equation (2.36) below, which is obtained by substituting into the incumbent HJB the expressions for the equilibrium incumbent R&D wage in Lemma 2.2.4.

$$r\tilde{V} = \tilde{\pi} - \hat{\tau}\tilde{V} + \max_{\substack{\mathbb{1}^{NCA} \in \{0,1\} \\ z \geq 0}} \left\{ \overbrace{z \left(\chi(\lambda - 1)\tilde{V} - \hat{w}_{RD} \right)}^{\mathbb{E}[\text{Benefit from R\&D}]} - \underbrace{(1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu\tilde{V}}_{\text{Net cost of not using NCA}} - \overbrace{\mathbb{1}^{NCA}\kappa_c\nu\tilde{V}}^{\text{Direct cost of NCA}} \right\}. \quad (2.36)$$

Equation (2.36) has an intuitive economic interpretation. The left-hand side is the equilibrium flow payoff on an asset with value $\tilde{V}$. On the right is the flow payoff of incumbency. The first term, $\tilde{\pi}$, is the flow profits of an incumbent. The term $-\hat{\tau}\tilde{V}$, is the expected capital loss from creative destruction by entrants. The term $\chi(\lambda - 1)\tilde{V}$ is the expected benefit per unit of R&D effort. The factor $\lambda - 1$ reflects the fact that the incumbent takes into account the opportunity cost of no longer producing with

¹⁷One way is to add heterogeneity in the ability to use NCAs. Another is to incorporate heterogeneity in κ_c , κ_e , or both.

the obsolete technology. The term $-\hat{w}_{RD}$ reflects the cost of R&D effort due to the contribution from the prevailing R&D wage.

The last two terms determine the optimal NCA policy. The first term $-(1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu\tilde{V}$ is the expected net cost to the incumbent from not using an NCA. It consists of two components. First, the term $-(1 - \mathbb{1}^{NCA})\nu\tilde{V}$ is the expected capital loss from creative destruction by employee spinouts. Second, the term $(1 - \mathbb{1}^{NCA})(1 - \kappa_e)\lambda\nu\tilde{V}$ is the equilibrium R&D wage discount when an NCA is not imposed. This term is positive because, in equilibrium, the R&D worker accepts a lower wage in return for an expected future payoff from spinout formation, by Lemma 2.2.4. Finally, the last term $-\mathbb{1}^{NCA}\kappa_c\nu\tilde{V}$ reflects is the direct cost of using an NCA. Incumbents choose the value of $\mathbb{1}^{NCA}$ which maximizes the term multiplying z .

Lemma 2.2.5. *In a symmetric BGP with $z > 0$,*

$$\tilde{V} = \frac{\hat{w}_{RD}}{\chi(\lambda - 1) - (1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu - \mathbb{1}^{NCA}\kappa_c\nu}. \quad (2.37)$$

Proof. The constant returns to scale in the incumbent innovation technology implies the incumbent must be indifferent if $z > 0$, i.e. the term multiplying z in (2.36) must equal zero. Solving for $\tilde{V}$ yields (2.37). $\square$

Equilibrium innovation and growth Finally, I use the results from the previous three sections to characterize the equilibrium R&D allocation and resulting growth rate. Using Proposition 2.2.2 and its corollary, the FOC for the entrant's optimization

problem, given in (2.27), becomes

$$\hat{\chi}\hat{z}^{-\psi}(1 - \kappa_e)\lambda\tilde{V} = \hat{w}_{RD} \quad (2.38)$$

Substituting for $\tilde{V}$ by using Lemma 2.2.5 yields an expression for entrant R&D,

$$\hat{z} = \left(\frac{\hat{\chi}(1 - \kappa_e)\lambda}{\chi(\lambda - 1) - (1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu - \mathbb{1}^{NCA}\kappa_e\nu} \right)^{1/\psi}. \quad (2.39)$$

Market clearing for R&D labor implies

$$z = \bar{L}_{RD} - \hat{z}. \quad (2.40)$$

If (2.40) implies that $z < 0$ then $z = 0$ in equilibrium. I return to this case below. Suppose for now that (2.40) is consistent with $z > 0$. Then growth is determined by the growth accounting equation,¹⁸

$$g = (\lambda - 1)(\tau + \tau^S + \hat{\tau}). \quad (2.41)$$

The Euler equation determines the interest rate according to

$$r = \theta g + \rho. \quad (2.42)$$

¹⁸A derivation can be found in Appendix 2.B.2.

Substituting the incumbent's FOC into the incumbent's HJB, and using the expression for the interest rate, yields the incumbent's value $\tilde{V}$, given by

$$\tilde{V} = \frac{\tilde{\pi}}{r + \hat{r}}. \quad (2.43)$$

Finally, the entrant optimality condition (2.38) determines the equilibrium value of $\hat{w}_{RD}$. If the above steps imply $z < 0$ or $\hat{z} \leq 0$, then $z = 0$ and $\hat{z} = \bar{L}_{RD}$. The rest of the derivation is the same as in the case that $z > 0$.

Finally, in order for equilibrium to be well-defined, household utility must be finite. This is ensured by the following assumption.

Assumption 1. $\rho > (1 - \theta)g$

In Assumption 1, g stands for the closed form expression for g . Namely, if $z > 0$ then

$$g = (\lambda - 1) \left(\left(\frac{\hat{\chi}(1 - \kappa_e \lambda)}{\chi(\lambda - 1) - \nu \min\{1 - (1 - \kappa_e)\lambda, \kappa_c\}} \right)^{(1-\psi)/\psi} + \left(\chi + (1 - \mathbb{1}_{\kappa_c < \bar{\kappa}_c})\nu \right) \left(\bar{L}_{RD} - \frac{\hat{\chi}(1 - \kappa_e \lambda)}{\chi(\lambda - 1) - \nu \min\{1 - (1 - \kappa_e)\lambda, \kappa_c\}} \right)^{1/\psi} \right). \quad (2.44)$$

Otherwise,

$$g = (\lambda - 1)\hat{\chi}\bar{L}_{RD}^{1-\psi}. \quad (2.45)$$

Lemma 2.2.6. *Under Assumption 1, the household's utility is finite on a symmetric BGP with growth rate g .*

Proof. Using $C(t) = C(0)e^{gt}$ on the BGP, the household's utility is

$$U = \mathcal{K} \int_0^\infty e^{-\rho t} e^{(1-\theta)gt} dt + \text{Constant}. \quad (2.46)$$

for some constant $\mathcal{K} > 0$. The integral $\int_0^\infty e^{-\rho t} e^{(1-\theta)gt} dt$ converges if and only if $\rho > (1 - \theta)g$. $\square$

Note that $\theta \geq 1$ implies Assumption 1. This is the empirically relevant case which I consider in the calibration. The next two assumptions are used in the statement of the main proposition.

Assumption 2. $0 < \left(\frac{\hat{\chi}(1-\kappa_e)\lambda}{\chi(\lambda-1)-(1-\mathbb{1}^{NCA})(1-(1-\kappa_e)\lambda)\nu-\mathbb{1}^{NCA}\kappa_c\nu} \right)^{1/\psi} < \bar{L}_{RD}$.

Assumption 2 ensures that $z > 0$ on the symmetric BGP. The term $\mathbb{1}^{NCA}$ is as defined in (2.35). Now I can state the main proposition.

Proposition 2.2.4. *If Assumption 1 holds and $\kappa_c \neq \bar{\kappa}_c$ (as defined in Proposition 2.2.3), there exists a symmetric BGP. There is a unique symmetric BGP, satisfying $z > 0$, if and only if Assumption 2 holds. If Assumption 2 fails to hold, then there exist infinitely many symmetric BGPs (with $z = 0$) that differ only in $\mathbb{1}_{jt}^{NCA}$.*

Proof. Here I offer a sketch of the proof; details can be found in Appendix 2.B.1. Existence follows because a symmetric BGP can be constructed following the derivation given in the main text. When Assumption 2 holds, the equilibrium expression for $\hat{z}$ is in $(0, \bar{L}_{RD})$. The constructed symmetric BGP therefore has $z > 0$ and is unique by construction, as each equilibrium condition has a unique solution given parameters and other equilibrium objects. If Assumption 2 does not hold, then

$z = 0$ and, by the same reasoning, all equilibrium variables are uniquely determined except for $\mathbb{1}_{jt}^{NCA}$. The latter is not pinned down by optimality because $z = 0$ implies that the NCA policy is irrelevant to the incumbent. $\square$

Note that if $\kappa_c = \bar{\kappa}_c$, then Proposition 2.2.3 does not restrict $\mathbb{1}^{NCA}$. Both possibilities are consistent with a symmetric equilibrium. Because $z > 0$ under Assumption 2, these two equilibria have different values of τ^S and therefore exhibit different aggregate growth rates. In fact, a continuum of symmetric BGPs can be constructed where, in each BGP, at any given time a constant fraction of incumbents have $\mathbb{1}_{jt}^{NCA} = 1$. These equilibria are explored in more detail in 2.B.2.

2.3 Calibration

2.3.1 Parameters

The model has 11 parameters, $\{\rho, \theta, \beta, \psi, \lambda, \chi, \hat{\chi}, \kappa_e, \kappa_c, \nu, \bar{L}_{RD}\}$. The two parameters θ, ψ are set externally. The elasticity parameter θ is set to 2, corresponding to a standard value used in the literature. The entrant R&D curvature parameter ψ is set to a value of 0.5 (the same as in Acemoglu and Cao 2015), corresponding to a quadratic cost. I consider robustness of the main result to the value of these and all other parameters in Section 2.D.1.

The remaining nine parameters are calibrated to match moments. The parameter $\bar{L}_{RD}$ is calibrated to data on the share of employment in R&D, from the NSF. The parameter β is set to match the profit to GDP ratio. The final seven parameters $\{\rho, \lambda, \chi, \hat{\chi}, \kappa_e, \kappa_c, \nu\}$ pertain to preferences (ρ) and to the innovation technology and

NCA usage (all others), and are chosen to match six moments from the data. One parameter, κ_c , is partially identified as $\kappa_c > \bar{\kappa}_c$ by the observation that $\tau^S > 0$. The remaining six parameters are exactly identified and the model reproduces the target moments exactly. I discuss the sources of identification in Section 2.3.3.

2.3.2 Targets

The targets of the calibration are displayed in Table 2.1. They consist of the labor productivity growth rate due to creative destruction and own-product innovation, the R&D to GDP ratio, the real return on the corporate sector, the share of growth coming from older firms improving their own products, the employment share of new firms engaging in creative destruction, and the employment share of R&D-induced WSOs. The last three targets are not directly observable in the data. I obtain values for them from previous work in the literature and from the empirical section of this paper.

Matching the productivity growth rate, R&D to GDP ratio and growth share of OI helps calibrate the efficiency of R&D in generating aggregate productivity growth through OI and CD. The real return, profit to GDP ratio and employment share of entering firms determines the discount factor and the reward to innovation. Further, the employment share of young firms helps identify the size of each innovation: at a constant contribution to aggregate growth, a lower share of employment at entering firms implies each innovation by an entering firm is smaller. Finally, matching the employment share of entering WSOs allows the model to capture the rate at which R&D by incumbents increases their likelihood of being replaced by a WSO.

Below, I discuss the calibration targets in more detail.

Growth rate due to CD and OI The growth rate is calibrated to the growth in labor productivity due to CD and OI, as calculated in Garcia-Macia et al. 2019 and Klenow and Li 2020. Their accounting procedure uses a structural model of firm dynamics and growth through own-product innovation, creative destruction and new variety creation (but with exogenous productivity growth) to infer the sources of growth from the economy-wide distribution of changes in sales and employment at the firm and establishment levels.¹⁹

Growth share of older firms The growth share of older firms improving their own products is calibrated to the growth share of OI as a fraction of OI and CD innovations, as estimated in Garcia-Macia et al. 2019 and Klenow and Li 2020. On average they find that, from 1982 to 2013, roughly 65% of CD + OI productivity growth was due to firms at least 6 years old. The computation of the corresponding model moment is described in 2.C.1.

R&D spending to GDP The data on R&D spending is from the National Patterns of R&D resources.²⁰ In the data, about half of R&D spending is wages for employees; in the model, the only input to R&D is labor. I opt to match the model’s aggregate R&D intensity to that in the data, including costs other than labor. This means that the model captures the full cost of innovation, but likely overestimates the aggregate

¹⁹The key identification assumptions are essentially that creative destruction, own-product innovation and new variety creation all have different implications for the cross-sectional and time-series joint distribution of firm and establishment employment, sales, and exit.

²⁰I take the average of business-funded R&D business-performed R&D.

labor earnings of R&D employees. The computation of the corresponding model moment is described in 2.C.1.

Interest rate The interest rate in the model corresponds to the discount factor used to price a risky firm. The annual real return on the S&P 500 in the time period 1984-2006 was 9.15%. BAA corporate bonds earned an annual real return of 7.58%. To calculate the excess return of all corporate liabilities, I take a weighted average of the the excess return of stock and equity using the sample period average debt to equity ratio of 58%, or a debt to market value of 37%. This implies an overall real return of 8.57%.

Profits to GDP The data the profit to GDP ratio comes from the BEA. I use the average ratio during the sample period of 1984-2006.

Employment share of young firms As discussed in Klenow and Li 2020, adjustment costs mean that, in the data, it can take several years for a new product to displace an old one. However, in the model, entrants that replace incumbents reach their mature size immediately upon entry, simplifying the model significantly. However, this does mean that, if the model matches the amount of employment in firms of age < 1 , it might underestimate the true impact on employment reallocation of each new cohort of firms. For this reason, I choose to target the employment share of firms age ≤ 6 .

In addition, I restrict attention only to incumbents and young firms engaging in creative destruction. Because all entry in the model is creative destruction, including

employment in entrants developing new varieties would overstate the rate of creative destruction. To do this, I turn to Garcia-Macia et al. 2019 and Klenow and Li 2020, which estimate the portion of growth coming from firms of different ages engaging in creative destruction, new variety creation, and own product improvement. They find that roughly 18% of employment is in firms age ≤ 6 during the sample period, and that between 30% and 70% of the growth from these firms is due to creative destruction, the rest due to new variety creation. However, in their framework, as in mine, a given amount of growth from creative destruction requires significantly more employment, as it destroys a previous incumbent. Using a value of $\lambda = 1.2$, for example, creative destruction requires 6 times more employment than new variety creation to generate the same amount of growth. Lower values of λ imply a larger adjustment. Using $\lambda = 1.2$ as a benchmark value, I calculate an employment share of young firms of 13.34% during the sample period. The calibrated value of λ will be 1.084, so a choice of $\lambda = 1.2$ in the calculation of this target is conservative. A lower choice here implies a higher share of employment in young firms and, as discussed in the robustness analysis of Appendix 2.D.1, this would strengthen my main result. The computation of the corresponding model moment is described in 2.C.1.

Spinout share of employment Finally, matching the employment share of spinouts which can be attributed to R&D allows the analysis to accurately capture the burden spinouts impose on incumbents as well as the overall importance of this phenomenon for innovation and productivity growth. As discussed in Chapter 1, R&D by parent firms can account for about 8.5% of employment at startups in the Venture Source. However, as with the employment share of young firms, I want to restrict

Table 2.1: Calibration targets

	Key parameter(s)	Target	Model
Profit (% GDP)	β	8.5%	8.5%
R&D emp. share	$\bar{L}_{RD}$	1%	1%
Real return	ρ	8.57%	8.57%
Growth rate	$\lambda, \chi, \hat{\chi}$	1.487%	1.487%
Age ≥ 6 growth share	$\chi, \hat{\chi}$	65%	65%
Age < 6 emp. share	$\lambda, \hat{\chi}$	13.34%	13.34%
Spinout emp. share	ν	10%	10%
R&D spending (% GDP)	$\chi, \hat{\chi}, \kappa_e$	1.35%	1.35%

attention to firms engaging in creative destruction. Some of the non-WSO startups are not engaged in creative destruction. The same type of argument as before yields an adjustment factor between $1/.93$ and $1/.7$, which implies that between 9% and 12% of creative destruction startup employment consists of WSOs. I choose a value of 10% for the calibration. The computation of the corresponding model moment is described in 2.C.1.

2.3.3 Identification

In this section, I discuss how the calibration identifies the parameters of the model. First, it is important to note that the relationship between the model parameters and the model-generated moments is non-linear and many parameters influence multiple moments. Figure 2.1 shows the elasticity of model moments to model parameters.²¹ All moments are influenced by multiple parameters. Note that the model is extremely sensitive to the log of λ . This is in part due to the fact that a proportional change

²¹This is computed as the jacobian matrix of the mapping that takes log parameters to log model moments.

in λ implies a much larger proportional change in $\lambda - 1$, which is the percentage by which an innovation increases quality.

The object that is most directly related to identification is the elasticity of inferred model parameters to targeted moments. This is shown in Figure A1.²² With this perspective, one can see that conclusions based on Figure 2.1 can be misleading. For example, while an increase in λ causes a large increase in the growth share of Age ≥ 6 firms, increasing the moment target decreases the estimated λ . Given all the moments that need to be matched, the calibration prefers to match the growth share of Age ≥ 6 firms by using a much higher χ and actually slightly lower λ . To complete the picture, Figure A3 augments Figure 2.1 with non-calibrated parameters included as both parameters and target moments. As before, Figure A2 inverts this matrix to obtain the elasticity of calibrated parameters to moment targets and non-calibrated parameters. This gives the complete picture of how the model parameters are inferred.

Based on this analysis, one can obtain an intuition regarding how the model parameters are pinned down by the calibration targets. The discount rate ρ is identified to simultaneously match the interest rate, growth rate and IES. The parameters $\beta, \bar{L}_{RD}$ are chosen to exactly match the profit share of GDP and the share of labor in R&D, respectively. The parameters $\lambda, \chi, \hat{\chi}$ are chosen to simultaneously match the growth rate g , the share of growth from firms at least six years old, and the employment share of firms less than six years old. Intuitively, these three measures determine the size and frequency of each innovation, as well as its attribution to incumbents or entrants. The parameter κ_e is distinguished from $\hat{\chi}$ by matching

²²This is calculated by inverting the matrix shown in the previous figure. This inverse is locally well-defined because the model is locally exactly identified by the target moments.

Table 2.2: Calibrated parameters

Parameter	Value	Description	Source
θ	2	$\theta^{-1} = \text{IES}$	External
ψ	0.5	Entrant R&D curvature	External
ρ	0.056	Discount rate	Internal
β	0.094	$\beta^{-1} = \text{EoS intermediate goods}$	Internal
λ	1.085	Quality ladder step size	Internal
χ	26.35	Incumbent R&D productivity	Internal
$\hat{\chi}$	0.461	Entrant R&D productivity	Internal
κ_e	0.740	Non-R&D entry cost	Internal
ν	0.431	Spinout generation rate	Internal
$\bar{L}_{RD}$	0.01	R&D labor allocation	Internal

the R&D to GDP ratio. Intuitively, in order to be consistent with equilibrium, the expected private return to entrant R&D must be the same as the real interest rate. Because entrant R&D has a high expected payoff, as it results in a monopoly, equilibrium requires a large cost. If R&D is the only cost, then the R&D spending to GDP ratio is counterfactually high.²³ Finally, the parameter ν is identified by matching the employment share of WSOs.

²³In this calibration, imposing $\kappa_e = 0$ means that best-fit R&D to GDP ratio is 1.9% rather than 1.35%. This is closely related to the main finding of Comin 2004.

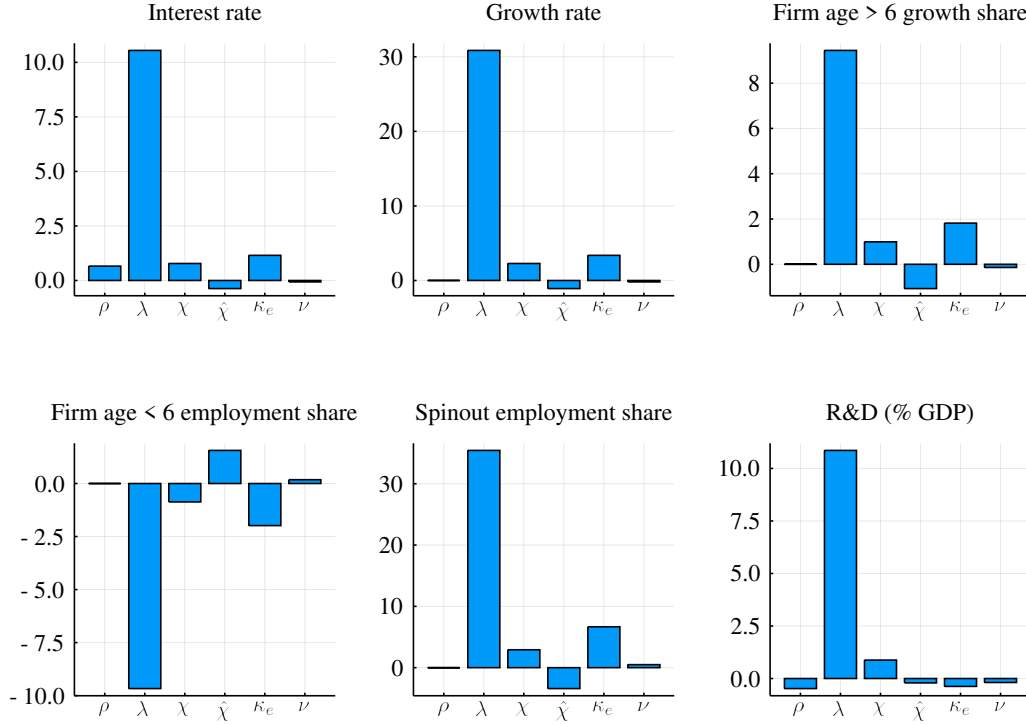


Figure 2.1: Plot showing the elasticity of model moments to model parameters. These elasticities are computed by taking the jacobian matrix of the mapping from log parameters to log model moments.

2.4 Welfare effect of NCA enforcement and other policies

In this section, I use the calibrated model as a laboratory for studying the effect of policies. I conduct a sequence of second-best analyses assuming the planner can control one or more parameters and/or Pigouvian taxes.²⁴ All comparisons below

²⁴I do not study the first-best allocation because of the fact that I have specified the model in terms of the private value of being an incumbent, which is only well-defined in a decentralized equilibrium. The model could be augmented – at the expense of requiring numerical solutions – to

are static comparisons between BGPs. Throughout, I assume that taxes (subsidies) are rebated to (financed by) the representative household in a lump-sum payment. Because there is no labor-leisure choice, this does not create any additional distortions in the economy.

The main exercise considers whether, and by how much, reducing barriers to the use of NCAs increases or decreases growth and welfare. Next, I consider a planner who can use R&D subsidies in order to illustrate how they can have an effect in this model even though the total supply of R&D labor is fixed. I then consider a planner who can target R&D subsidies to own-product innovation, a policy which can substitute for the enforcement of NCAs in this setting. Finally, I consider a planner who can simultaneously subsidize own-product innovation and control the enforcement of NCAs.²⁵

2.4.1 Preliminaries

Welfare Social welfare is simply the representative household's lifetime utility,²⁶

$$\tilde{W} = \int_0^\infty e^{-\rho t} \frac{C(t)^{1-\theta} - 1}{1-\theta} ds. \quad (2.47)$$

accommodate the study of a first-best problem by simply specifying the NCA cost and the entry cost as linear in $\bar{q}_{jt}$ rather than $V(j, t|\bar{q}_{jt})$.

²⁵A subsidy to intermediate goods revenue or production labor expenditures can also improve welfare by correcting the static inefficiency emanating from the monopolistic competition markup. As this is not the focus of this paper, I do not consider it in the policy analysis.

²⁶This should be written in terms of W_t , the welfare at time t . I ignore this detail in the interest of simplicity and without loss of generality, since the model grows at constant rate and therefore $W_t = e^{(1-\theta)gt} \tilde{W}$.

Using $C(t) = \tilde{C}e^{gt}$ on the BGP and integrating yields

$$\tilde{W} = \frac{\tilde{C}^{1-\theta}}{(1-\theta)(\rho - g(1-\theta))} + \kappa(\rho, \theta), \quad (2.48)$$

where $\kappa(\rho, \theta)$ is a constant that depends only on preferences. Social welfare can thus be decomposed into a *growth* channel (g) and an *level* channel ($\tilde{C}$). Higher values for either imply higher welfare. The term $\tilde{C}$ is referred to as the level of consumption because it is equal to $C(t)/Q(t)$ on the BGP. It can be further decomposed using

$$\tilde{C} = \tilde{Y} - \overbrace{(\hat{\tau} + \tau^S)\kappa_e \lambda \tilde{V}}^{\text{Creative destruction cost}} - \underbrace{\mathbb{1}^{NCA} z \kappa_c \nu \tilde{V}}_{\text{NCA enforcement cost}}, \quad (2.49)$$

so that steady-state consumption is flow output of the final good minus the final goods cost of creative destruction and of NCA enforcement.²⁷

Consumption-equivalent change in welfare To make welfare comparisons quantitatively meaningful, I compare welfare across BGPs in consumption-equivalent (CE) terms. This is defined as follows. For a given equilibrium ε , let $\tilde{C}_\varepsilon, g_\varepsilon, \tilde{W}_\varepsilon$ denote the level of consumption given Q_t , the growth rate of consumption, and the time-0 present value of household utility, respectively. Following the derivation of welfare in (2.48), one can write

$$\tilde{W}_\varepsilon = f(\tilde{C}_\varepsilon, g_\varepsilon) + \kappa(\rho, \theta), \quad (2.50)$$

²⁷To interpret the entry cost as a transfer, replace (2.49) with $\tilde{C} = \tilde{Y} - \mathbb{1}^{NCA} z \kappa_c \nu \tilde{V}$.

where

$$f(x, y) = \frac{x^{1-\theta}}{(1-\theta)(\rho - y(1-\theta))}, \quad (2.51)$$

Now consider an equilibrium ε' such that $\tilde{W}_\varepsilon < \tilde{W}_{\varepsilon'}$. The CE welfare improvement from equilibrium ε to equilibrium ε' is the permanent increase in consumption in ε that would achieve the same utility as ε' . More precisely, define $\hat{C}_{\varepsilon, \varepsilon'}$ such that

$$f(\hat{C}_{\varepsilon, \varepsilon'}, g_\varepsilon) = f(\tilde{C}_{\varepsilon'}, g_{\varepsilon'}). \quad (2.52)$$

The CE percentage welfare improvement of ε' over ε is the percentage increase from $\tilde{C}_\varepsilon$ to $\hat{C}_{\varepsilon, \varepsilon'}$. For $\theta > 1$ (the case of interest in this paper), a $\frac{\xi}{\theta-1}\%$ CE welfare improvement results from an $\xi\%$ decrease in the absolute value of $\tilde{W} - \kappa(\rho, \theta)$.²⁸

Table 2.3: Effect of reduction in κ_c on growth, level of consumption, and welfare

Measure	Variable	$\kappa_c > \bar{\kappa}_c$	$\kappa_c = 0$	Chg.
Growth	g	1.487%	1.696%	0.21 p.p.
Level	$\tilde{C}$	0.784	0.787	0.39%
Welfare	$\tilde{W}$			3.24% (CE)

2.4.2 NCA cost κ_c

The first policy I study is the effect of reducing κ_c . I interpret this as loosening restrictions on the use of NCAs. Note that, as discussed in Section 2.3, the fact that there are spinouts in the data partially identifies $\kappa_c > \bar{\kappa}_c$. Intuitively, according to the model, the spinouts in the data result from the fact that the NCAs that could have been used to prevent them were either too costly to enforce or legally prohibited. Therefore, to study the effect of reducing barriers to the enforcement of NCAs, I compare the calibrated BGP ($\kappa_c > \bar{\kappa}_c$) to the BGP that obtains when $\kappa_c = 0$. I interpret the latter to a case when there are no legal barriers to the use of NCAs.

²⁸For $\theta < 1$, a $\frac{\xi}{1-\theta}\%$ CE welfare improvement results from a $\xi\%$ increase in $\tilde{W} - \kappa(\rho, \theta)$. The case $\theta = 1$ corresponds to log utility, in which case

$$\tilde{W} = \frac{\rho \log(\tilde{C}) + g}{\rho^2} \quad (2.53)$$

In this case, there is no simple correspondence to obtain CE welfare changes, but they are easy to compute directly. Under the null policy, initial consumption is $\tilde{C}$ and growth is g . Under the new policy, initial consumption is $\tilde{C}^+$ and growth is g^+ . The CE welfare change is $\frac{\tilde{C}^* - \tilde{C}}{\tilde{C}}$, where $\tilde{C}^*$ is defined by

$$\frac{\rho \log(\tilde{C}^*) + g}{\rho^2} = \frac{\rho \log(\tilde{C}^+) + g^+}{\rho^2} \quad (2.54)$$

Table 2.4: Decomposition of effect of reducing κ_c on growth and R&D

Measure	Variable	$\kappa_c > \bar{\kappa}_c$	$\kappa_c = 0$	Chg.
Growth				
	g	1.487%	1.696%	0.21 p.p.
incumbents	$(\lambda - 1)\tau$	1.20%	1.47%	0.27 p.p.
entrants	$(\lambda - 1)\hat{\tau}$	0.26%	0.23%	-0.03 p.p.
spinouts	$(\lambda - 1)\tau^S$	0.02%	0%	-0.02 p.p.
R&D				
incumbents (%)	$z/\bar{L}_{RD}$	54.0%	65.8%	11.8 p.p.
entrants (%)	$\hat{z}/\bar{L}_{RD}$	46.0%	34.2%	-11.8 p.p.

One might imagine that there is some fundamental cost $\underline{\kappa}_c$ of using an NCA even in a jurisdiction that imposes no barriers to its use. For simplicity, I assume $\underline{\kappa}_c = 0$.

The results are displayed in Table 2.3. Compared to the BGP with $\kappa_c > \bar{\kappa}_c$, the BGP with $\kappa_c = 0$ has higher growth and initial consumption, implying a 3.24% increase in welfare in consumption-equivalent terms. Table 2.4 shows a decomposition of the sources of growth in the $\kappa_c > \bar{\kappa}_c$ and $\kappa_c = 0$ equilibria. When $\kappa_c = 0$, a higher share of R&D labor is allocated to own-product innovation and there is no longer entry by spinouts. Intuitively, having access to free NCAs ($\kappa_c = 0$) makes own-product innovation effectively less costly than when NCAs are prohibitively expensive ($\kappa_c > \bar{\kappa}_c$) and incumbents face the risk of employee spinout formation. Holding prices constant at their $\kappa_c > \bar{\kappa}_c$ levels, a shift to $\kappa_c = 0$ induces incumbents to demand more R&D labor. To clear the market, the equilibrium compensation to R&D labor must increase. The net effect is a shift in the allocation of R&D labor to own-product innovation.

Figure 2.2 visually decomposes the effect of reducing κ_c on the growth rate and the level of consumption. The top row shows the allocation of R&D and the growth rate that results. For high values of κ_c the growth rate is low. As soon as $\kappa_c < \bar{\kappa}_c$, NCAs are used, eliminating spinout entry and reducing the BGP growth rate by a discrete amount. Note that there is no discrete change in the allocation of R&D when κ_c crosses this threshold because incumbents are indifferent between using and not using an NCA when $\kappa_c = \bar{\kappa}_c$. As κ_c is reduced further, the cost of own-product innovation declines (in partial equilibrium), inducing a shift of R&D labor as described in the previous paragraph. Next, the bottom row shows the entry and NCA costs paid and the level of consumption $\tilde{C}$ that results. Plots showing other equilibrium objects (the innovation rate, incumbent value, the interest rate, and the R&D wage) are displayed in Figure A5.

Equilibrium R&D misallocation

To understand how a higher share of R&D labor allocated to own-product innovation increases growth by enough to outweigh the contribution of spinouts, consider the equilibrium marginal effect on innovation (and hence growth) of the two types of R&D. For creative destruction, this is given by

$$\frac{d}{d\hat{z}}\hat{\tau} = (1 - \psi)\hat{\chi}\hat{z}^{-\psi}. \quad (2.55)$$

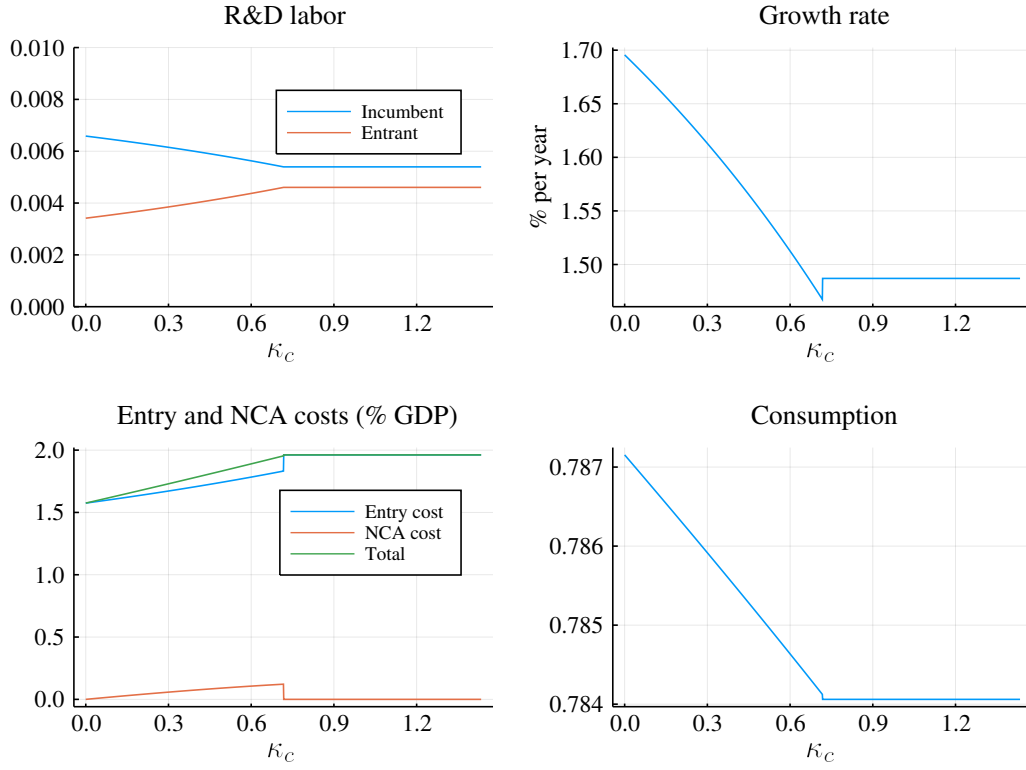


Figure 2.2: Effect of varying κ_c on key equilibrium variables. The top-left panel shows R&D labor allocated to incumbents (own-product innovation) and entrants (creative destruction). The top-right panel shows the aggregate productivity growth rate. The bottom-left panel shows the entry costs paid by entrants and spinouts as well as the direct NCA enforcement cost. Finally, the bottom-right panel shows the level of consumption.

For own-product innovation, this is given by

$$\frac{d}{dz}\tau = \chi + (1 - \mathbb{1}^{NCA})\nu. \quad (2.56)$$

A reallocation of R&D labor to own-product innovation increases the BGP growth rate if and only if

$$\frac{d}{dz}\tau > \frac{d}{d\hat{z}}\hat{\tau}. \quad (2.57)$$

Using (2.55), (2.56), and the expression for equilibrium $\hat{z}$ given in (2.39), the inequality (2.57) becomes

$$1 > \overbrace{\frac{\lambda - 1}{\lambda}}^{\text{Business stealing}} \times \underbrace{(1 - \psi)}_{\text{Congestion}} \times \overbrace{\frac{1}{1 - \kappa_e}}^{\text{Entry cost}} \times \overbrace{\frac{\chi}{\chi + (1 - \mathbb{1}^{NCA})\nu}}^{\text{Spinout formation}} \times \underbrace{\frac{\chi(\lambda - 1) - (1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu - \mathbb{1}^{NCA}\kappa_e\nu}{\chi(\lambda - 1)}}_{\text{Effective cost of R\&D}}. \quad (2.58)$$

In the calibrated BGP, the RHS of (2.58) has a value of 0.13. This means that, in equilibrium, a marginal unit of R&D labor allocated to own-product innovation is 7.9 times as productive in generating growth as a marginal unit of R&D labor allocated to creative destruction. Hence there is a significant amount of misallocation of R&D in equilibrium. This fact is driving the significant growth gains from the R&D reallocation in response to a reduction in κ_c . Below I discuss the economic intuition behind each term in (2.58).

First, the term $\frac{\lambda-1}{\lambda} < 1$ reflects the *business stealing* externality. Creative destruction by entrants imposes a negative externality on the incumbent. This means that entrants are able to earn the required private return on R&D while experiencing a lower marginal innovation rate per unit of R&D. It is decreasing in λ . Intuitively, a lower value of λ means that a higher fraction of the private return to creative destruction is stolen business. Quantitatively, this effect is the main driver of the growth increase from setting $\kappa_c = 0$. In the calibration, $\frac{\lambda-1}{\lambda} \approx 0.08$.²⁹

Next, the term $1 - \psi < 1$ reflects the *congestion* externality. As discussed in the exposition of the model, individual entrants impose a negative externality on the expected returns of other entrants. This congestion externality leads to an overallocation of R&D to entrants. In the calibration, $1 - \psi = 0.5$. Higher values of ψ imply stronger congestion externality, exacerbating the equilibrium misallocation of R&D.

The term $\frac{1}{1-\kappa_e} \geq 1$ reflects the additional *entry cost* paid by entrants upon innovating. It reduces the private payoff from each creative destruction innovation. To ensure that the expected return of creative destruction is the equilibrium rate of return, the expected number of innovations from a given amount of R&D in creative destruction must increase. Therefore, this mechanism works against the previous two effects, and in the calibration, with a value of $\frac{1}{1-\kappa_e} \approx 3.84$, reduces the extent

²⁹In models with duopolistic competition between incumbents, such as Aghion, Nick Bloom, et al. 2005, this effect would be attenuated because own-product innovation by a market leader has a business-stealing component.

of misallocation of R&D. On the other hand, a higher value of κ_e also reduces the efficiency of creative destruction R&D by increasing the entry cost.³⁰

Next, the term $\frac{\chi}{\chi+(1-\mathbb{1}^{NCA})\nu} \leq 1$ reflects the contribution to the productivity of own-product innovation stemming from *entry by WSOs*. If $\mathbb{1}^{NCA} = 0$ and $\nu > 0$, the term is strictly less than 1. R&D by incumbents has a positive growth externality through its effect on the entry of spinouts. Because these spinouts are not appropriated by the incumbent, in equilibrium a marginal unit of incumbent R&D generates more total innovations. In the calibration, this term is 0.98. This is not very strong as spinout innovations constitute only 1.7% of innovations resulting from incumbent R&D. If $\mathbb{1}^{NCA} = 1$ or $\nu = 0$ this term is equal to 1.

Finally, the term $\frac{\chi(\lambda-1)-(1-\mathbb{1}^{NCA})(1-(1-\kappa_e)\lambda)\nu-\mathbb{1}^{NCA}\kappa_c\nu}{\chi(\lambda-1)}$ reflects the fact that entrants pay a different *effective cost of R&D* than the incumbent. When $\kappa_c > \bar{\kappa}_c$, so $\mathbb{1}^{NCA} = 0$, the inequality $1 - (1 - \kappa_e)\lambda > 0$ means that the expected harm from future spinouts exceeds the equilibrium wage discount from not using an NCA – i.e., spinouts are bilaterally suboptimal. In equilibrium, this means that incumbents pay a higher effective cost per unit of R&D. When $\kappa_c < \bar{\kappa}_c$, so that $\mathbb{1}^{NCA} = 1$, incumbents pay the entrant R&D wage plus the NCA enforcement cost; as long as $\kappa_c > 0$, incumbents have a strictly higher effective cost of R&D. In equilibrium, the marginal private returns to R&D must equate. Hence, marginal R&D allocated to creative destruction

³⁰For the value of κ_e in the calibration, further increasing κ_e on net reduces the benefit to reallocating R&D. This occurs because, for high values of κ_e , $\frac{1}{1-\kappa_e}$ becomes highly sensitive to further increases in the value of κ_e , while the cost of entry always increases linearly in κ_e (ignoring quantitatively small changes in $\tilde{V}$).

must generate innovations at a lower rate. In the calibration, $\mathbb{1}^{NCA} = 0$ and this term is equal to 0.86.³¹

Magnitude of overall effect on growth of reducing κ_c The preceding discussion shows why there is any scope for a reduction in κ_c to increase growth: inequality (2.58) implies that the derivative of the growth rate with respect to a reallocation of R&D to own-product innovation is positive. However, the overall magnitude of the increase in growth is the integral of this marginal effect of reallocation minus the reduction growth from the stifling of spinout formation by NCAs. This integral, in turn, is increasing in the sensitivity of the R&D allocation is to a given change in $\kappa_c\nu$, as well as how much $\kappa_c\nu$ can be reduced from the calibration-implied value of $\bar{\kappa}_c$.

The sensitivity of the R&D allocation to a given change in $\kappa_c\nu$ is determined by the price-elasticity of R&D demand by entrants and incumbents: a higher price-elasticity for either implies a larger R&D reallocation. Note that while a higher price-elasticity of R&D of entrants implies more reallocation, it also implies a weaker congestion externality, reducing the growth impact of a given amount of reallocation of R&D. I consider curvature in the incumbent innovation function in the robustness check in the appendix, discussed briefly in the next subsection.

The extent to which $\kappa_c\nu$ can be reduced is determined by $\bar{\kappa}_c = 1 - (1 - \kappa_e)\lambda$ and ν . A higher inferred value of $\bar{\kappa}_c$ means the shift to $\kappa_c = 0$ is a larger reduction in costs. Intuitively, if the calibration finds that creative destruction is more costly per

³¹Alternatively, if $1 - (1 - \kappa_e)\lambda < 0$, spinouts are bilaterally efficient and, in equilibrium, incumbents benefit from spinouts *ex ante*. As a consequence, incumbents have a lower effective cost of R&D than entrants and the effect is reversed.

spinout, it implies that there are larger barriers to the use of NCAs (a larger value of κ_c). A higher value of ν amplifies the beneficial R&D allocation effect of reducing κ_c from $\bar{\kappa}_c$ to zero as incumbent R&D incentives depend on $\kappa_c\nu$.

Finally, a higher value of ν amplifies the growth decrease from setting $\kappa_c < \bar{\kappa}_c$ which results from the direct reduction in innovation by WSOs. This loss of growth is equal to $(\lambda - 1)\nu\bar{z}$, where $\bar{z}$ is the R&D allocation to own-product innovation in the equilibrium with $\kappa_c = \bar{\kappa}_c$. It also amplifies the disincentive to R&D spending posed by WSO formation when NCAs are prohibitively expensive. Hence, the growth-increasing and growth-decreasing effects of reducing κ_c are amplified by ν in a similar way.

Robustness

I study the robustness of the main result to variation in both target moments and uncalibrated parameters in Appendix 2.D.1. First, I show that the welfare result is quantitatively similar when considering entry costs as transfers to the financial intermediary, at 2.86% in CE terms. As noted previously, this interpretation increases the social value of within-industry spinouts. The fact that the result is quantitatively similar demonstrates that the key result is not driven by a large resource cost of spinout entry. Second, I show that the result is robust to an augmented model where the incumbent has a decreasing returns to scale innovation production function. The growth increase in that case is similar to the baseline, at 0.177 percentage points, and the welfare increase is also quantitatively similar at 2.65% in CE terms. Next, I show that the result that setting $\kappa_c = 0$ increases growth is robust to a 16% standard deviation of uncertainty in the calibration targets. Finally, I show that the growth

and welfare results are in fact reversed when the model is forced to match a 5%, rather than 13.34%, employment share of young firms. This occurs largely due to a higher calibrated value of λ (about 1.59), which works to bring the right-hand side of inequality (2.58) much closer to 1. As a result, the improvement in the R&D allocation is not enough to offset the reduction in innovation by spinouts. Growth declines by 0.02 percentage points and welfare decreases by 0.23% in CE terms.

2.4.3 R&D subsidy

The first alternative policy I consider is a subsidy to R&D spending. This is a natural class of policy to study due to its significant magnitude the United States, where all told the Federal government funds about 15% of business-performed R&D.³²

First, I briefly discuss the equilibrium that obtains in the presence of an R&D subsidy; the details of the derivation are in 2.B.3. Suppose that the planner subsidizes R&D spending at rate T_{RD} (tax if $T_{RD} < 0$). In this case, in a symmetric BGP the incumbent's HJB becomes

$$\begin{aligned}
 (r + \hat{\tau})\tilde{V} = \tilde{\pi} + \max_{\substack{\mathbb{1}^{NCA} \in \{0,1\} \\ z \geq 0}} \Big\{ & \underbrace{z \left(\chi(\lambda - 1)\tilde{V} - (1 - T_{RD}) \right)}_{\text{R\&D Subsidy}} \underbrace{\left(\hat{w}_{RD} - (1 - \mathbb{1}^{NCA})(1 - \kappa_e)\lambda\nu\tilde{V} \right)}_{\text{Incumbent R\&D wage}} \\
 & - \underbrace{(1 - \mathbb{1}^{NCA})\nu\tilde{V} - \mathbb{1}^{NCA}\kappa_c\nu\tilde{V}}_{\text{Loss of incumbency from spinout formation}} \Big\}. \tag{2.59}
 \end{aligned}$$

³²In the United States, the marginal R&D subsidy rate is between 15 and 20%, which is claimed via deduction on corporate income taxes. The deduction can be carried forward twenty years. These R&D subsidies are applied only to R&D spending above a firm-specific base which is defined in reference to past levels of R&D and firm sales. Taking this into account direct R&D subsidies offer about a 5% effective subsidy. In addition, federal and local governments directly fund about 10% of private business-performed R&D.

Given this HJB, equilibrium usage of NCAs is analogous to the model with no R&D subsidies, although with a different threshold value, given by

$$\tilde{\kappa}_c = 1 - (1 - T_{RD})(1 - \kappa_e)\lambda. \quad (2.60)$$

Note that the threshold $\tilde{\kappa}$ is increasing in the subsidy to R&D spending T_{RD} . At $T_{RD} = 1$, the threshold is $\tilde{\kappa} = 1$. This means that, provided $\bar{\kappa}_c < \kappa_c < 1$, a sufficiently large R&D subsidy induces incumbents to use NCAs in equilibrium. Note that this is the relevant case, as $\kappa_c \geq 1$ implies that NCAs are prohibitively expensive for any strictly positive noncompete wage premium.

Using $z > 0$ and the incumbent FOC as before, the equilibrium R&D allocation is

$$\hat{z} = \left(\frac{\hat{\chi}(1 - \kappa_e)\lambda}{\chi(\lambda - 1) - \nu(\mathbb{1}^{NCA}\kappa_c + (1 - \mathbb{1}^{NCA})(1 - (1 - T_{RD})(1 - \kappa_e)\lambda))} \right)^{1/\psi}, \quad (2.61)$$

$$z = \bar{L}_{RD} - \hat{z}. \quad (2.62)$$

Inspection of the expression for $\hat{z}$ shows that, when $\mathbb{1}^{NCA} = 0$, $\hat{z}$ increases in T_{RD} . Intuitively, an increase in the R&D subsidy from T_{RD}^0 to T_{RD}^1 reduces the wage expenses paid for R&D by the factor $1 - \frac{1 - T_{RD}^1}{1 - T_{RD}^0}$ for both incumbents and entrants. However, the incumbent's effective cost of R&D also includes the increased likelihood of creative destruction by an employee spinout, which is not subsidized. Therefore, the incumbent's effective cost of R&D is reduced by a factor $\tilde{\tau}_{RD} < 1 - \frac{1 - T_{RD}^1}{1 - T_{RD}^0}$. In general equilibrium, an increase in T_{RD} results in R&D labor being reallocated to entrants. Furthermore, for large enough subsidies, $\kappa_c < \tilde{\kappa}_c$ so the incumbent uses

Table 2.5: Effect of R&D subsidy on growth, NCAs, level of consumption and welfare

Measure	Variable	R&D Subsidy (%)			
		0	10	20	30
Growth	g	1.49%	1.48%	1.46%	1.44%
Level	$\tilde{C}$	0.784	0.784	0.783	0.783
NCAs	$\mathbb{1}^{NCA}$	0	0	0	1
Δ Welfare (CE)	$\tilde{W}$		-0.18%	-0.36%	-0.73%

NCAs. This occurs because she prefers to pay employees using subsidized wages rather than through future employee spinouts, the cost of which – i.e., the expected lost profit from being replaced by a spinout – is not subsidized.

Turning to the quantitative exercise, recall that the model can only set identify $\kappa > \bar{\kappa}_c$ in order to match the fact that there are spinouts. However, if κ_c is much larger than $\bar{\kappa}_c$, any changes to the incentives for NCAs induced by policy will have no observable effect on the equilibrium. In order to be able to illustrate these effects, in this and all subsequent exercises I assume that $\kappa_c = 1.1\bar{\kappa}_c$.³³

Table 2.5 shows how the equilibrium growth rate g , consumption level $\tilde{C}$, usage of NCAs $\mathbb{1}^{NCA}$, and welfare $\tilde{W}$ are affected by R&D subsidies. The growth rate declines and the level of consumption is unaffected. When R&D subsidies are raised to 30%, incumbents use NCAs. Welfare declines overall at an increasing rate, particularly when NCAs are used and spinouts no longer enter. Table 2.6 decomposes the sources

³³In a model with incumbent heterogeneity, such as non-degenerate distribution of κ_e and κ_c across goods j , one could avoid making such a stark assumption by identifying certain moments of this distribution by matching the fraction of workers who are bound by NCAs. Still, some assumptions on the form of this distribution would likely be necessary, as a single balanced growth path cannot does not characterize it.

Table 2.6: Decomposition of effect of R&D subsidies on growth and R&D

Measure	Variable	R&D Subsidy (%)			
		0	10	20	30
Growth	g	1.49%	1.48%	1.46%	1.44%
incumbents	$(\lambda - 1)\tau$	1.20%	1.19%	1.18%	1.17%
entrants	$(\lambda - 1)\hat{\tau}$	0.26%	0.27%	0.27%	0.27%
spinouts	$(\lambda - 1)\tau^S$	0.02%	0.02%	0.02%	0%
R&D					
incumbents (%)	$z/\bar{L}_{RD}$	54.0%	53.4%	52.8%	52.4%
entrants (%)	$\hat{z}/\bar{L}_{RD}$	46.0%	46.6%	47.2%	47.6%

of growth and allocation of R&D. As in the case of varying κ_c , the growth decrease results from a reallocation of R&D. Because the reallocation is to entrants (creative destruction) and away from incumbents (own-product innovation) in this case, the growth rate decreases due to (2.58). Figure 2.3 shows how key equilibrium objects respond to R&D subsidies. In particular, growth declines continuously with the R&D subsidy until point at which $\kappa_c < \tilde{\kappa}_c$, where there is a discrete fall in the growth rate as spinouts no longer enter. Plots describing how the entire equilibrium responds are displayed in Figure A6.

Because the supply of R&D labor is inelastic in this model, it is not surprising that untargeted R&D subsidies are do not lead to higher growth rates. However, in a model without within-industry spinouts, untargeted R&D would simply have no effect on the equilibrium. This exercise shows that the general equilibrium adjustment of R&D wages can lead to a counterproductive misallocation of R&D in response to R&D subsidies. To the extent that the supply of R&D labor is not perfectly elastic,

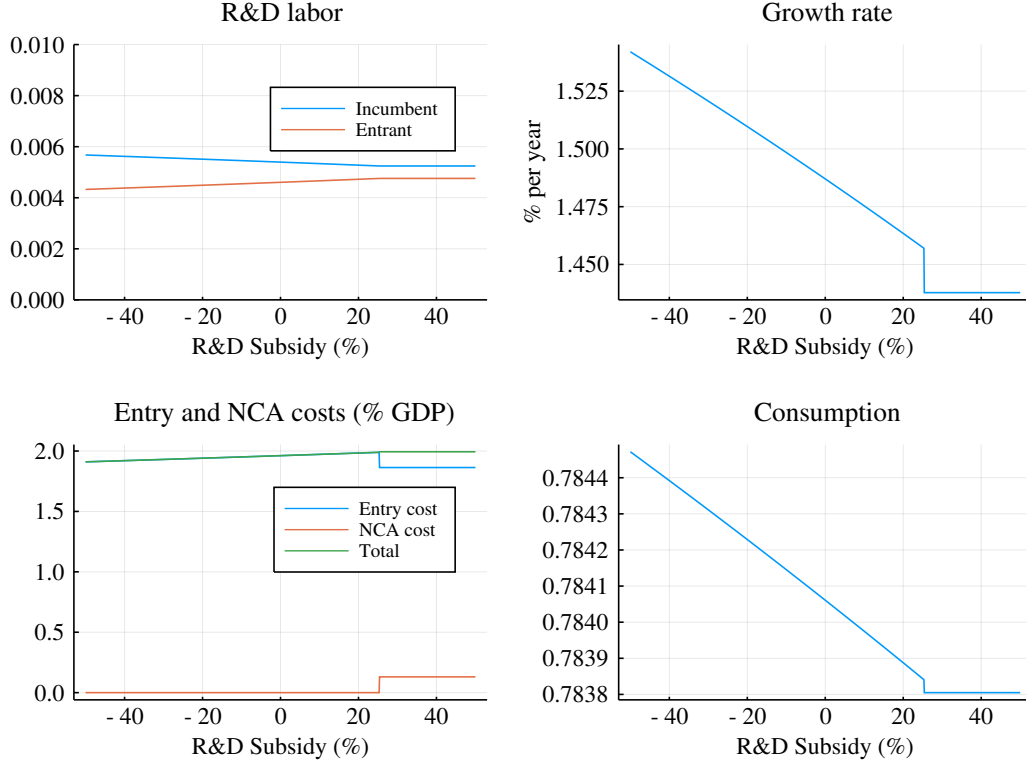


Figure 2.3: Summary of equilibrium for baseline parameter values and various values of T_{RD} . This assumes that $\kappa_c = 1.1\bar{\kappa}_c$. The top-left panel shows R&D labor allocated to incumbents (own-product innovation) and entrants (creative destruction). The top-right panel shows the aggregate productivity growth rate. The bottom-left panel shows the entry costs paid by entrants and spinouts as well as the direct NCA enforcement cost. Finally, the bottom-right panel shows the level of consumption.

this mechanism can play a role. It implies that untargeted R&D subsidies have a weaker positive effect (i.e., less “bang for buck”) than in a standard model without within-industry spinouts and NCAs.

It is important to note that, as with the results concerning NCA enforcement, this result is driven by the fact that the firms most efficient at the marginal unit of R&D are also the firms that are most concerned about competition from WSOs.

2.4.4 Targeted R&D subsidy

The fact that reducing κ_c increases growth by reallocating R&D to own-product innovation suggests that targeted R&D subsidies can be a substitute to enforcing NCAs. Suppose that the planner can subsidize own-product R&D while excluding creative destruction R&D, denoting this subsidy $T_{RD,I} < 1$ (tax if $T_{RD,I} < 0$). The new equilibrium conditions are derived in Appendix 2.B.3. Here I simply discuss the equilibrium use of NCAs and the R&D allocation. As before, NCAs are used in equilibrium as long as κ_c is lower than a threshold, this time given by

$$\hat{\kappa}_c = 1 - (1 - T_{RD,I})(1 - \kappa_e)\lambda. \quad (2.63)$$

Therefore, just as with untargeted R&D subsidies, large enough targeted R&D subsidies have the unintended effect of inducing the use of NCAs. The equilibrium

R&D allocation is given by

$$\hat{z} = \left(\frac{(1 - T_{RD,I})\hat{\chi}(1 - \kappa_e)\lambda}{\chi(\lambda - 1) - \nu(\mathbb{1}^{NCA}\kappa_c + (1 - \mathbb{1}^{NCA})(1 - (1 - T_{RD,I})(1 - \kappa_e)\lambda))} \right)^{1/\psi}, \quad (2.64)$$

$$z = \bar{L}_{RD} - \hat{z}. \quad (2.65)$$

Note that when $\mathbb{1}^{NCA} = 0$, the term $T_{RD,I}$ appears in both the numerator and denominator with the same negative sign. Specifically, the numerator has the term $-\hat{\chi}(1 - \kappa_e)\lambda T_{RD,I}$ and the denominator has the term $-(1 - \mathbb{1}^{NCA})\nu(1 - \kappa_e)\lambda T_{RD,I}$. The term in the numerator results from the fact that incumbents demand more R&D labor in response to subsidies, which in equilibrium increases the wage and thus reduces incentives for entrants to do R&D. The term in the denominator is analogous to the term in the case of untargeted R&D subsidies. It results from the fact that when $\mathbb{1}^{NCA} = 0$, incumbents effectively do not receive the full R&D subsidy because part of their cost of R&D is the expected loss of business due to employee spinout formation. Hence, the second effect dampens the first effect, but does not overturn it.

To see this formally, differentiate (2.64) with respect to $T_{RD,I}$ and simplify, yielding

$$\frac{d\hat{z}^\psi}{dT_{RD,I}} = \frac{-\chi(\lambda - 1) + \nu}{g(T_{RD,I}, \chi, \lambda, \kappa_c, \kappa_e)^2}, \quad (2.66)$$

where g is a function of $T_{RD,I}$ and certain model parameters. As $g^2 > 0$, it follows that $\frac{d\hat{z}^\psi}{dT_{RD,I}}$ is strictly negative if and only if

$$\chi(\lambda - 1) > \nu. \quad (2.67)$$

Table 2.7: Effect of targeted R&D subsidy on growth, NCAs, level of consumption and welfare

Measure	Variable	Targeted R&D Subsidy (%)			
		0	20	40	60
Growth	g	1.49%	1.80%	2.01%	2.17%
NCAs	$\mathbf{1}^{NCA}$	0	0	1	1
Level	$\tilde{C}$	0.784	0.787	0.789	0.792
Δ Welfare (CE)	$\tilde{W}$		4.47%	7.45%	9.63%

Table 2.8: Decomposition of effect of targeted R&D subsidy on growth and R&D

Measure	Variable	Targeted R&D Subsidy (%)			
		0	20	40	60
Growth	g	1.49%	1.80%	2.01%	2.17%
incumbents	$(\lambda - 1)\tau$	1.21%	1.56%	1.85%	2.05%
entrants	$(\lambda - 1)\hat{\tau}$	0.26%	0.21%	0.16%	0.11%
spinouts	$(\lambda - 1)\tau^S$	0.02%	0.02%	0.00%	0.00%
R&D					
incumbents (%)	$z/\bar{L}_{RD}$	54.0%	70.0%	82.9%	92.4%
entrants (%)	$\hat{z}/\bar{L}_{RD}$	46.0%	30.0%	17.1%	7.6%

The condition (2.67) holds in the calibration. In fact, it is also a necessary condition for $\tau^S > 0$ in the symmetric BGP.³⁴

To quantify the effect of a targeted R&D subsidy, I return to the calibrated model. Table 2.7 shows how the equilibrium growth rate g , consumption level $\tilde{C}$, and welfare are affected by subsidies to incumbent R&D. The growth rate and level of consumption increase. When R&D subsidies are raised to 40%, incumbents are

³⁴If it did not hold, there is no positive equilibrium wage at which incumbents would demand R&D labor not bound by an NCA.

induced to use NCAs. Welfare increases at a decreasing rate, particularly when NCAs are used and spinouts no longer enter. Table 2.8 decomposes the effect on growth and R&D. As targeted R&D subsidies are increased, R&D is reallocated to incumbents. Recalling the derivation above, this occurs because $\chi(\lambda - 1) - \nu > 0$. Because inequality (2.58) holds, this increases growth.

Figure 2.4 plots the effect of targeted R&D subsidies on the R&D allocation, growth rate, entry and NCA costs, and the level of consumption. Note how there is a discrete decline in the growth rate for targeted R&D subsidies above 25% due to the use of NCAs they induce. Consumption increases in the targeted R&D subsidy due to a decline in entry costs. When NCAs begin to be used in equilibrium, there is a very small discrete fall in consumption as the rising NCA cost is largely offset by a declining cost of entry by spinouts. Additional plots showing how other equilibrium objects are affected by targeted R&D subsidies can be found in Figure A7.

Before turning to the optimal policy analysis, note that in this model a tax on R&D allocated to creative destruction would serve a very similar role to the targeted R&D subsidy studied in this section. In fact, denoting the tax by $T_{RD,E}$, the R&D allocation in that case would be

$$\hat{z} = \left(\frac{(1 + T_{RD,E})^{-1} \hat{\chi}(1 - \kappa_e)\lambda}{\chi(\lambda - 1) - \nu(\mathbb{1}^{NCA}\kappa_c + (1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda))} \right)^{1/\psi}, \quad (2.68)$$

$$z = \bar{L}_{RD} - \hat{z}. \quad (2.69)$$

In this case, the R&D allocation is more sensitive because there is no dampening secondary effect and there is no change in the NCA usage threshold $\hat{\kappa}_c$. I have

chosen to focus on the subsidy to incumbent R&D for two reasons. First, it may be impossible to implement a tax on R&D expenditures in reality as a firm can simply claim that it is not conducting R&D. The regulator would need to check whether firms are engaging in creative destruction R&D. Contrast that with the case of R&D subsidies, which require the regulator only to evaluate the validity of firms' claimed R&D expenses. Second, the equivalence of these two policies would no longer hold in a model with an elastic aggregate supply of R&D labor. In that case, a tax on R&D, even if targeted, would reduce the total amount of R&D.

2.4.5 NCA cost κ_c and targeted R&D subsidy

While the targeted R&D subsidy analyzed in the last section can increase growth and welfare significantly, it also induces the use of NCAs, dampening its positive effect on growth and welfare. This suggests that the optimal policy involves targeted R&D subsidies and an increase in the cost of NCA enforcement. Therefore, in this section I consider a planner who can simultaneously control κ_c and $T_{RD,I}$.

Table 2.9 shows the effect on growth of various combinations of κ_c and $T_{RD,I}$. For low values of $T_{RD,I}$, growth is maximized when $\kappa_c = 0$, as in the baseline case. As $T_{RD,I}$ increases, the benefit of reducing κ_c declines. In this sense, targeted R&D subsidies substitute for the enforcement of NCAs. With targeted R&D subsidies at 40%, the growth increase from setting $\kappa_c = 0$ is less than one third of its value without subsidies. At 60% subsidies, the growth increase from $\kappa_c = 0$ is reduced to 0.01 percentage points. For intermediate values of κ_c , the growth rate is slightly lower. When targeted R&D subsidies are at 80%, reducing κ_c to zero reduces the

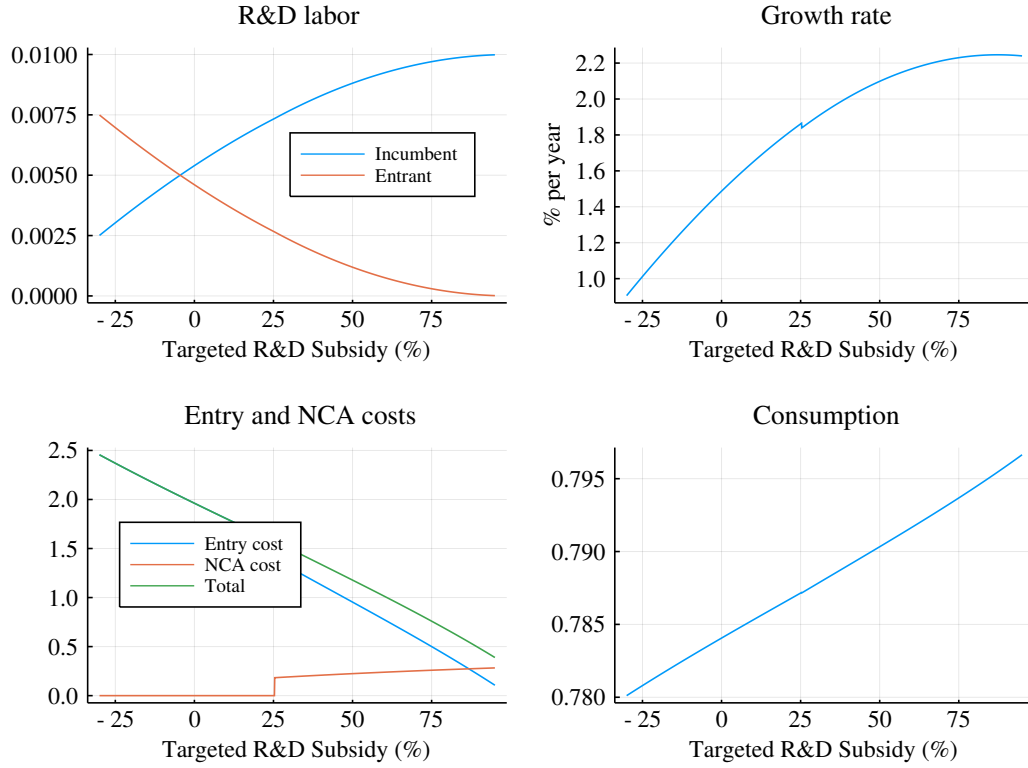


Figure 2.4: Summary of equilibrium for baseline parameter values and various values of $T_{RD,I}$. This assumes that $\kappa_c = 1.1\bar{\kappa}_c$. The top-left panel shows R&D labor allocated to incumbents (own-product innovation) and entrants (creative destruction). The top-right panel shows the aggregate productivity growth rate. The bottom-left panel shows the entry costs paid by entrants and spinouts as well as the direct NCA enforcement cost. Finally, the bottom-right panel shows the level of consumption.

growth rate. The threshold occurs at a targeted R&D subsidy of 62% (not shown in the table). Growth is maximized at 2.282% when the targeted R&D subsidy is 88% and NCAs are banned.

Table 2.10 shows the CE welfare percent improvement relative to the baseline calibration. The same results are shown in a contour plot in Figure 2.5. Compared to growth, enforcing NCAs remains socially optimal for higher values of the targeted R&D subsidy. This results from the reduced entry costs. In the table, enforcing NCAs reduces welfare only with an 80% targeted subsidy; the specific threshold in this case is a targeted subsidy of 77%. The peak improvement in welfare is achieved with a high targeted R&D subsidy of around 95% and a ban on NCAs. The welfare increase resulting from this policy is 11.44% in CE terms. One caveat is that the welfare gain from banning NCAs is relatively small at only about 0.15 percentage points in CE terms.

In Appendix 2.D.2 I consider how this result changes when interpreting the entry costs of creative destruction as transfers to the financial intermediary. The finding that the growth and welfare optimal policies involve large targeted R&D subsidies and a ban on NCAs still holds. However, the optimal targeted R&D subsidy is lower, at about 88%, and the threshold targeted R&D subsidy beyond which banning NCAs is socially optimal drops from 78% to 62%. Moreover, the gain from banning NCAs in the optimal policy is three times larger, at 0.45 percentage points. Intuitively, treating entry costs as transfers makes creative destruction by entrants and spinouts more socially valuable. Hence, the optimal allocation involves less reallocation of R&D

Table 2.9: Growth rate for various values of κ_c and $T_{RD,I}$

		$\kappa_c/\bar{\kappa}_c$			
		0	.5	1	1.5
$T_{RD,I}$ (%)	0	1.70%	1.59%	1.49%	1.49%
	20	1.92%	1.86%	1.78%	1.80%
	40	2.09%	2.05%	2.02%	2.03%
	60	2.20%	2.19%	2.17%	2.19%
	80	2.24%	2.24%	2.24%	2.28%
	90	2.24%	2.24%	2.24%	2.28%

Table 2.10: Welfare improvement from varying κ_c and targeted R&D subsidy

		$\kappa_c/\bar{\kappa}_c$			
		0	.5	1	1.5
$T_{RD,I}$ (%)	0	3.24%	1.70%	0%	0%
	20	6.47%	5.53%	4.35%	4.47%
	40	8.79%	8.25%	7.60%	7.74%
	60	10.31%	10.03%	9.71%	9.95%
	80	11.12%	10.98%	10.82%	11.17%
	90	11.27%	11.16%	11.04%	11.42%

towards own-product innovation and the benefit from banning NCAs and therefore allowing spinout formation is greater.

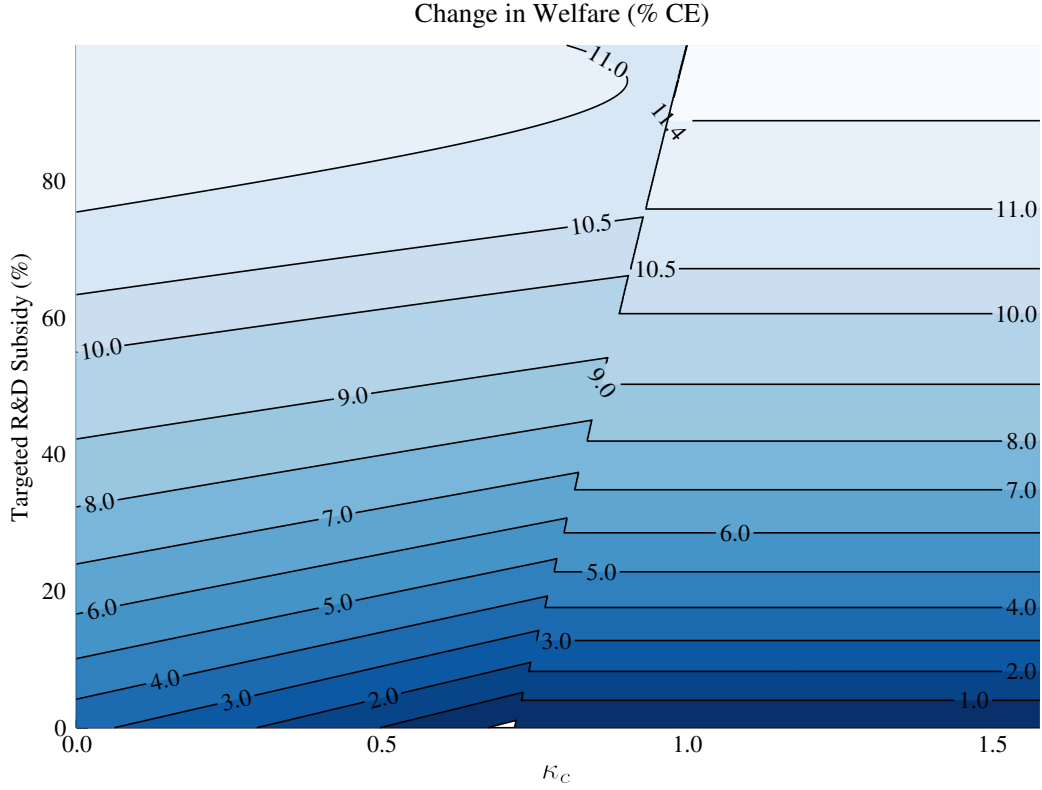


Figure 2.5: Summary of equilibrium for baseline parameter values and various values of $T_{RD,I}$ and κ_c . The optimal policy improves welfare by 11.44% in consumption-equivalent terms.

2.5 Conclusion

This chapter studies the effect of NCAs on growth and welfare. It makes several contributions. It extends a textbook model of endogenous growth with creative destruction to allow for within-industry spinouts and noncompete agreements. The augmented model offers some new theoretical insights about the effects of noncompete enforcement on growth and welfare. When calibrated to the firm-level relationship between R&D and employee spinouts estimated in Chapter 1, findings from the

growth accounting literature, and standard aggregate data, it suggests that reducing barriers to the usage of NCAs can significantly increase growth and welfare. It reaches this conclusion even in a model where there is a fixed supply of the input to R&D due to an inferred equilibrium misallocation of R&D labor to creative destruction, in turn resulting from strong inferred business stealing and congestion externalities of creative destruction.

The analysis also finds some novel implications of policies aimed at increasing growth. R&D subsidies may reduce growth by shifting R&D labor to firms engaging in creative destruction. They also induce the use of NCAs. R&D subsidies targeted at own-product innovation improve the allocation of R&D but continue to induce the socially inefficient use of NCAs. Hence, it is optimal to combine targeted subsidies to own-product innovation with a ban on the use of NCAs.

The model can be extended in several ways, at the cost of requiring a numerical solution. As mentioned in the text, the aggregate supply of R&D labor can be made price-elastic so that aggregate R&D responds to its private return. The model can be extended with heterogeneity in the cost of using noncompetes κ_c and the cost of creative destruction κ_e , yielding a fraction of incumbents using NCAs in equilibrium. The model can then be disciplined with data on the prevalence of noncompetes and used to analyze the effect of small changes in NCA enforcement. Finally, the model can be augmented with catch-up innovation and limit pricing. The model can then be disciplined with data on the variation of markups and concentration by state-level NCA enforceability.³⁵

³⁵This is the approach taken in Baslandze 2019. I discuss how my work differs from hers in the literature review of the introduction.

References

- Acemoglu, Daron (2009). *Introduction to Modern Economic Growth*. Princeton University Press.
- Acemoglu, Daron, Ufuk Akcigit, et al. (Nov. 2018). “Innovation, Reallocation, and Growth”. *American Economic Review* 108.11, pp. 3450–3491.
- Acemoglu, Daron and Dan Cao (May 2015). “Innovation by entrants and incumbents”. *Journal of Economic Theory* 157, pp. 255–294.
- Aghion, Philippe, Nick Bloom, et al. (2005). “Competition and Innovation: An Inverted-U Relationship”. *The Quarterly Journal of Economics* 120.2, pp. 701–728.
- Aghion, Philippe and Peter Howitt (1992). “A Model of Growth Through Creative Destruction”. *Econometrica* 60.2, pp. 323–351.
- Akcigit, Ufuk and William R. Kerr (Mar. 2018). “Growth through Heterogeneous Innovations”. *Journal of Political Economy* 126.4, pp. 1374–1443.

- Anton, James J. and Dennis A. Yao (1994). “Expropriation and Inventions: Appropriable Rents in the Absence of Property Rights”. *The American Economic Review* 84.1, pp. 190–209.
- (1995). “Start-ups, Spin-offs, and Internal Projects”. *Journal of Law, Economics, & Organization* 11.2, pp. 362–378.
- (Aug. 2002). “The Sale of Ideas: Strategic Disclosure, Property Rights, and Contracting”. *Review of Economic Studies* 69.3, pp. 513–531.
- Arrow, Kenneth (1962). *Economic Welfare and the Allocation of Resources for Invention*. NBER Chapters. National Bureau of Economic Research, Inc, pp. 609–626.
- Babina, Tania and Sabrina T Howell (July 2019). “Entrepreneurial Spillovers from Corporate R&D”. *NBER Working Paper*, p. 76.
- Balasubramanian, Natarajan et al. (May 12, 2020). “Locked In? The Enforceability of Covenants Not to Compete and the Careers of High-Tech Workers”. *Journal of Human Resources*. Publisher: University of Wisconsin Press, 1218–9931R1.
- Baslandze, Salome (2019). “Spinout Entry, Innovation, and Growth”. *Working Paper*.
- Bishara, Norman and Evan Starr (June 29, 2016). *The Incomplete Noncompete Picture*. SSRN Scholarly Paper ID 2782137. Rochester, NY: Social Science Research Network.

- Bloom, Nicholas, Mark Schankerman, and John van Reenen (2013). “Identifying Technology Spillovers and Product Market Rivalry”. *Econometrica* 81.4, pp. 1347–1393.
- Chatterjee, Satyajit and Esteban Rossi-Hansberg (2012). “Spinoffs and the Market for Ideas”. *International Economic Review* 53.1, pp. 53–93.
- Colombo, Luca et al. (2013). “Does Easy Start-Up Formation Hamper Incumbents’ R&D Investment? A Theoretical and Empirical Analysis”. *SSRN Electronic Journal*.
- Comin, Diego (2004). “R&D: A Small Contribution to Productivity Growth”. *Journal of Economic Growth* 9.4. Publisher: Springer, pp. 391–421.
- Conti, Raffaele (2014). “Do non-competition agreements lead firms to pursue risky R&D projects?” *Strategic Management Journal* 35.8, pp. 1230–1248.
- Doraszelski, Ulrich and Jordi Jaumandreu (Oct. 1, 2013). “R&D and Productivity: Estimating Endogenous Productivity”. *The Review of Economic Studies* 80.4. Publisher: Oxford Academic, pp. 1338–1383.
- Franco, April M. and Matthew F. Mitchell (2008). “Covenants not to Compete, Labor Mobility, and Industry Dynamics”. *Journal of Economics & Management Strategy* 17.3, pp. 581–606.
- Franco, April Mitchell and Darren Filson (Dec. 2006). “Spin-outs: knowledge diffusion through employee mobility”. *The RAND Journal of Economics* 37.4, pp. 841–860.

- Gabaix, Xavier (Sept. 2, 2009). “Power Laws in Economics and Finance”. *Annual Review of Economics* 1.1, pp. 255–294.
- Garcia-Macia, Daniel, Chang-Tai Hsieh, and Peter J. Klenow (2019). “How Destructive Is Innovation?” *Econometrica* 87.5, pp. 1507–1541.
- Garmaise, Mark J. (Aug. 2011). “Ties that Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment”. *The Journal of Law, Economics, and Organization* 27.2, pp. 376–425.
- Gompers, Paul, Josh Lerner, and David Scharfstein (2005). “Entrepreneurial Spawning: Public Corporations and the Genesis of New Ventures, 1986 to 1999”. *The Journal of Finance* 60.2, pp. 577–614.
- Griliches, Zvi (1979). “Issues in Assessing the Contribution of Research and Development to Productivity Growth”. *The Bell Journal of Economics* 10.1. Publisher: [RAND Corporation, Wiley], pp. 92–116.
- (1992). “The Search for R&D Spillovers”. *The Scandinavian Journal of Economics* 94. Publisher: [Wiley, The Scandinavian Journal of Economics], S29–S47.
- Grossman, Gene M. and Elhanan Helpman (1991). “Quality Ladders in the Theory of Growth”. *The Review of Economic Studies* 58.1, pp. 43–61.
- Hall, Bronwyn H., Jacques Mairesse, and Pierre Mohnen (Jan. 1, 2010). “Chapter 24 - Measuring the Returns to R&D”. *Handbook of the Economics of Innovation*. Ed. by

Bronwyn H. Hall and Nathan Rosenberg. Vol. 2. Handbook of the Economics of Innovation, Volume 2. North-Holland, pp. 1033–1082.

Harrison, Rupert et al. (July 1, 2014). “Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries”. *International Journal of Industrial Organization* 35, pp. 29–43.

Jeffers, Jessica (May 2018). *The Impact of Restricting Labor Mobility on Corporate Investment and Entrepreneurship*. SSRN Scholarly Paper ID 3040393. Rochester, NY: Social Science Research Network.

Jones, Charles I. and John C. Williams (1998). “Measuring the Social Return to R & D”. *The Quarterly Journal of Economics* 113.4. Publisher: Oxford University Press, pp. 1119–1135.

Klenow, Peter J. and Huiyu Li (Apr. 20, 2020). *Innovative Growth Accounting*. w27015. National Bureau of Economic Research.

Klepper, Steven (Apr. 2007). “Disagreements, Spinoffs, and the Evolution of Detroit as the Capital of the U.S. Automobile Industry”. *Management Science* 53.4, pp. 616–631.

Klette, Tor Jakob and Samuel Kortum (Oct. 2004). “Innovating Firms and Aggregate Innovation”. *Journal of Political Economy* 112.5, pp. 986–1018.

- Lentz, Rasmus and Dale T. Mortensen (2008). “An Empirical Model of Growth through Product Innovation”. *Econometrica* 76.6. Publisher: [Wiley, Econometric Society], pp. 1317–1373.
- Marx, Matt, Jasjit Singh, and Lee Fleming (2015). “Regional disadvantage? Employee non-compete agreements and brain drain”. *Research Policy* 44.2, pp. 394–404.
- Marx, Matt, Deborah Strumsky, and Lee Fleming (Apr. 2009). “Mobility, Skills, and the Michigan Non-Compete Experiment”. *Management Science* 55.6, pp. 875–889.
- Mohnen, Pierre and Bronwyn H. Hall (2013). “Innovation and Productivity: An Update”. *Eurasian Business Review* 3.1. Publisher: Eurasia Business and Economics Society, pp. 47–65.
- Romer, Paul M. (Oct. 1986). “Increasing Returns and Long-Run Growth”. *Journal of Political Economy* 94.5, pp. 1002–1037.
- (Oct. 1, 1990). “Endogenous Technological Change”. *Journal of Political Economy* 98.5. Publisher: The University of Chicago Press, S71–S102.
- Samila, Sampsa and Olav Sorenson (July 2010). “Venture Capital, Entrepreneurship, and Economic Growth”. *The Review of Economics and Statistics* 93.1, pp. 338–349.
- Shi, Liyan (Jan. 2018). “Restrictions on Executive Mobility and Reallocation: The Aggregate Effect of Non-Competition Contracts”. *Working Paper*.

- Starr, Evan (May 2018). *Consider This: Training, Wages, and the Enforceability of Covenants Not to Compete*. SSRN Scholarly Paper ID 2556669. Rochester, NY: Social Science Research Network.
- Starr, Evan, Natarajan Balasubramanian, and Mariko Sakakibara (Feb. 2018). “Screening Spinouts? How Noncompete Enforceability Affects the Creation, Growth, and Survival of New Firms”. *Management Science* 64.2, pp. 552–572.
- Starr, Evan, J. J. Prescott, and Norman Bishara (Jan. 2019). *Noncompetes in the U.S. Labor Force*. SSRN Scholarly Paper ID 2625714. Rochester, NY: Social Science Research Network.
- (Sept. 18, 2020). *The Behavioral Effects of (Unenforceable) Contracts*. SSRN Scholarly Paper ID 2858637. Rochester, NY: Social Science Research Network.
- Stuart, Toby E. and Olav Sorenson (2003). “Liquidity Events and the Geographic Distribution of Entrepreneurial Activity”. *Administrative Science Quarterly* 48.2, pp. 175–201.
- Uhlig, Harald (1996). “A Law of Large Numbers for Large Economies”. *Economic Theory* 8.1. Publisher: Springer, pp. 41–50.

Appendix

2.A Appendix of figures

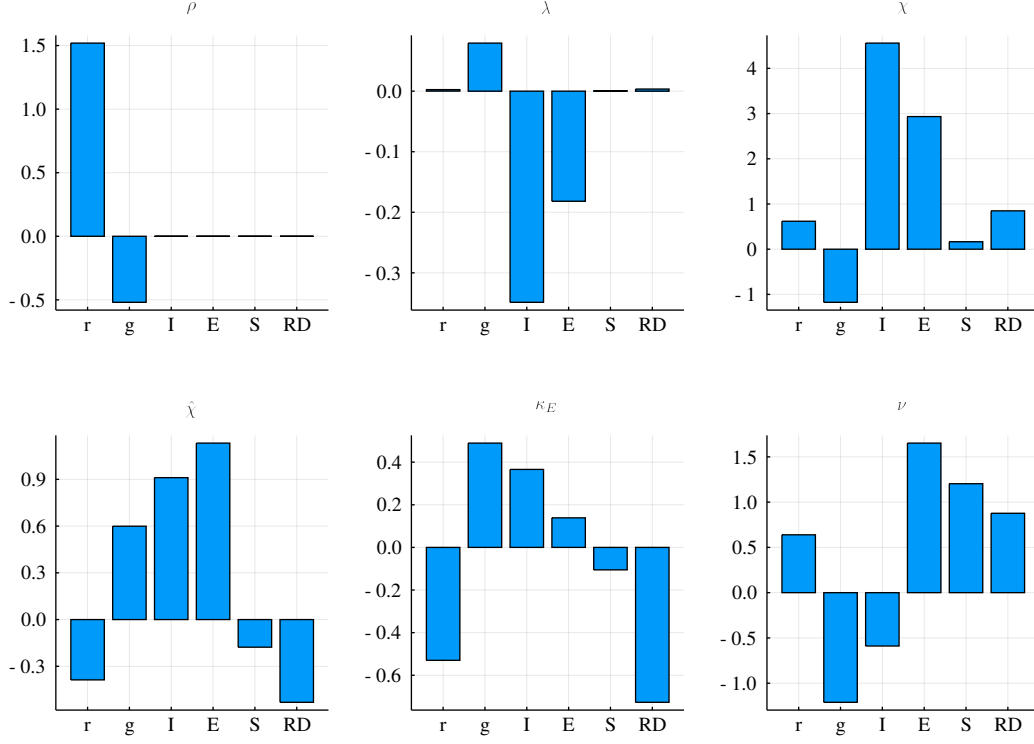


Figure A1: Plot showing the elasticity of parameters to moments. It is computed by inverting the jacobian matrix of the mapping from log parameters to log model moments (whose entries comprise the previous figure). These elasticities, along with estimates of the noisiness of the moments used in the calibration, can be used to estimate confidence intervals for the parameters in the model, and thereby for the welfare comparison in question. On each subplot, the horizontal axis labels refer, from left to right, to the interest rate, the growth rate, the share of growth in firms age > 6 (I for incumbent), the share of growth in firms age < 6 (E for entrant), the share of employment in spinouts, and the R&D to GDP ratio.

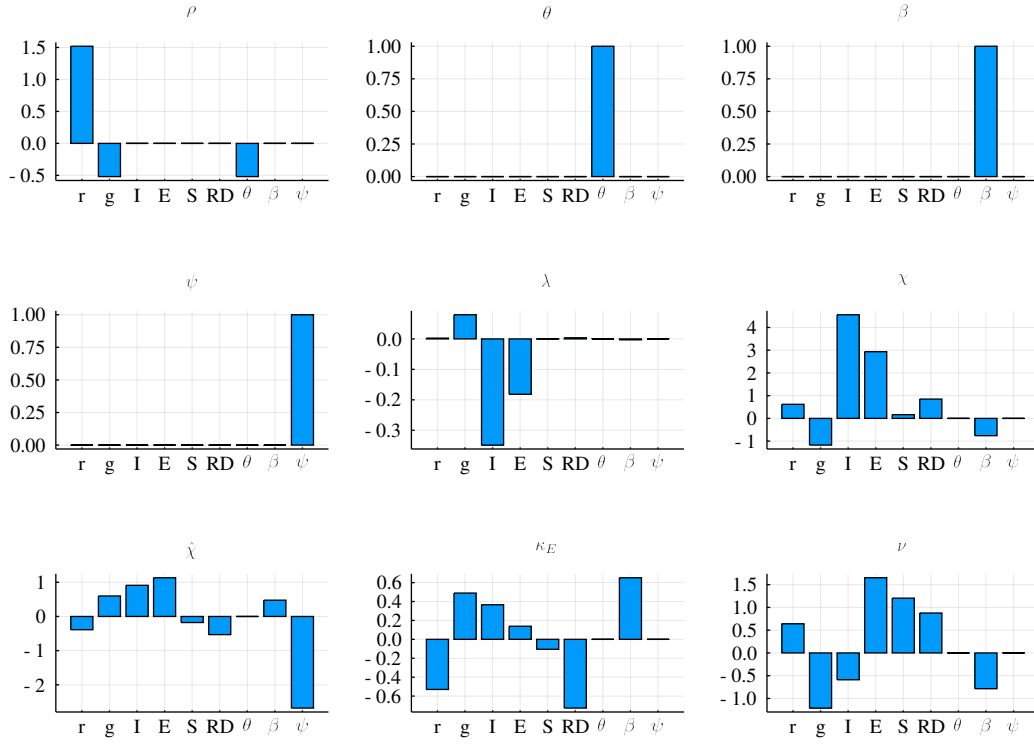


Figure A2: Same as Figure A1, but now including non-calibrated parameters. As before, this calculated by inverting the jacobian displayed in Figure A3. On each subplot, the horizontal axis labels refer, from left to right, to the interest rate, the growth rate, the share of growth in firms age > 6 (I for incumbent), the share of growth in firms age < 6 (E for entrant), the share of employment in spinouts, and the R&D to GDP ratio.

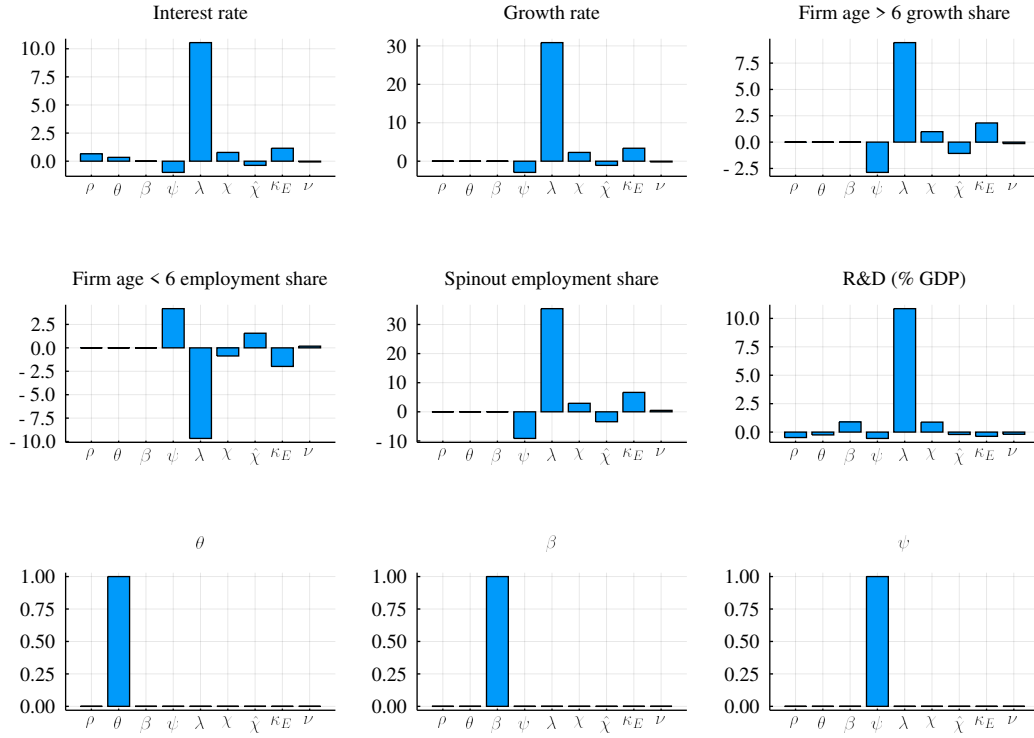


Figure A3: Plot showing the elasticity of moments to model parameters, including parameters chosen externally θ, β, ψ . These non-calibrated parameters are added in as effective moments to be matched, allowing the sensitivity of calibrated parameters $\rho, \lambda, \chi, \hat{\chi}, \kappa_E, \nu$ to these parameters to be computed by simply inverting this matrix, as before.

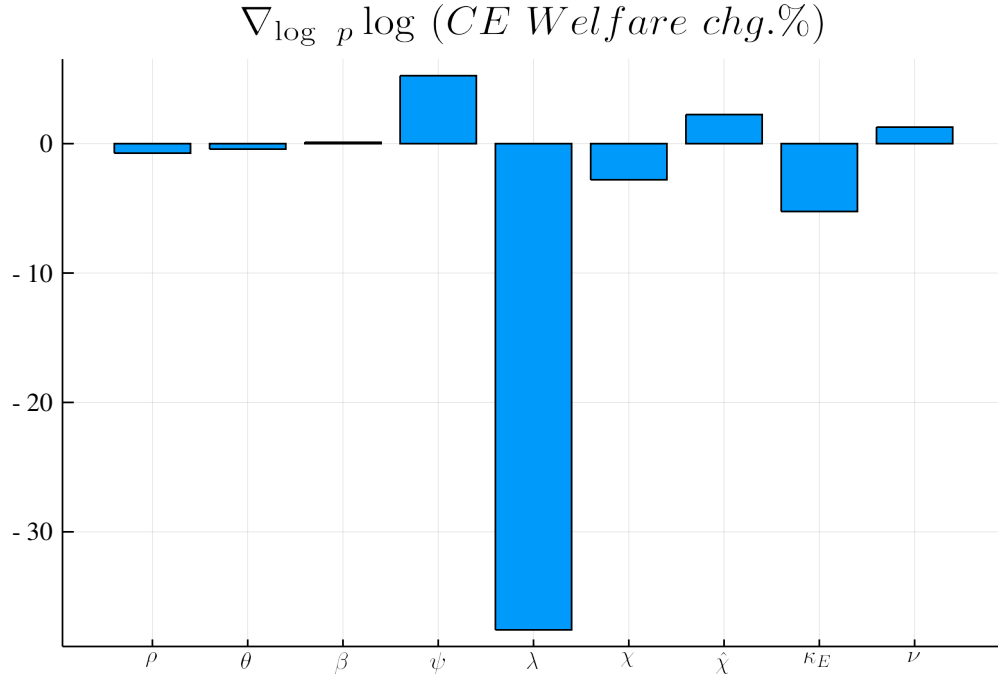


Figure A4: Sensitivity of welfare comparison to model parameters. This is $\nabla_p W$, where $W(p)$ maps log parameters to the log of the percentage change in BGP consumption which is equivalent to the change in welfare from changing κ_c from $\kappa_c > \bar{\kappa}_c$ to $\kappa_c = 0$ (i.e. going from banning to frictionlessly enforcing NCAs).

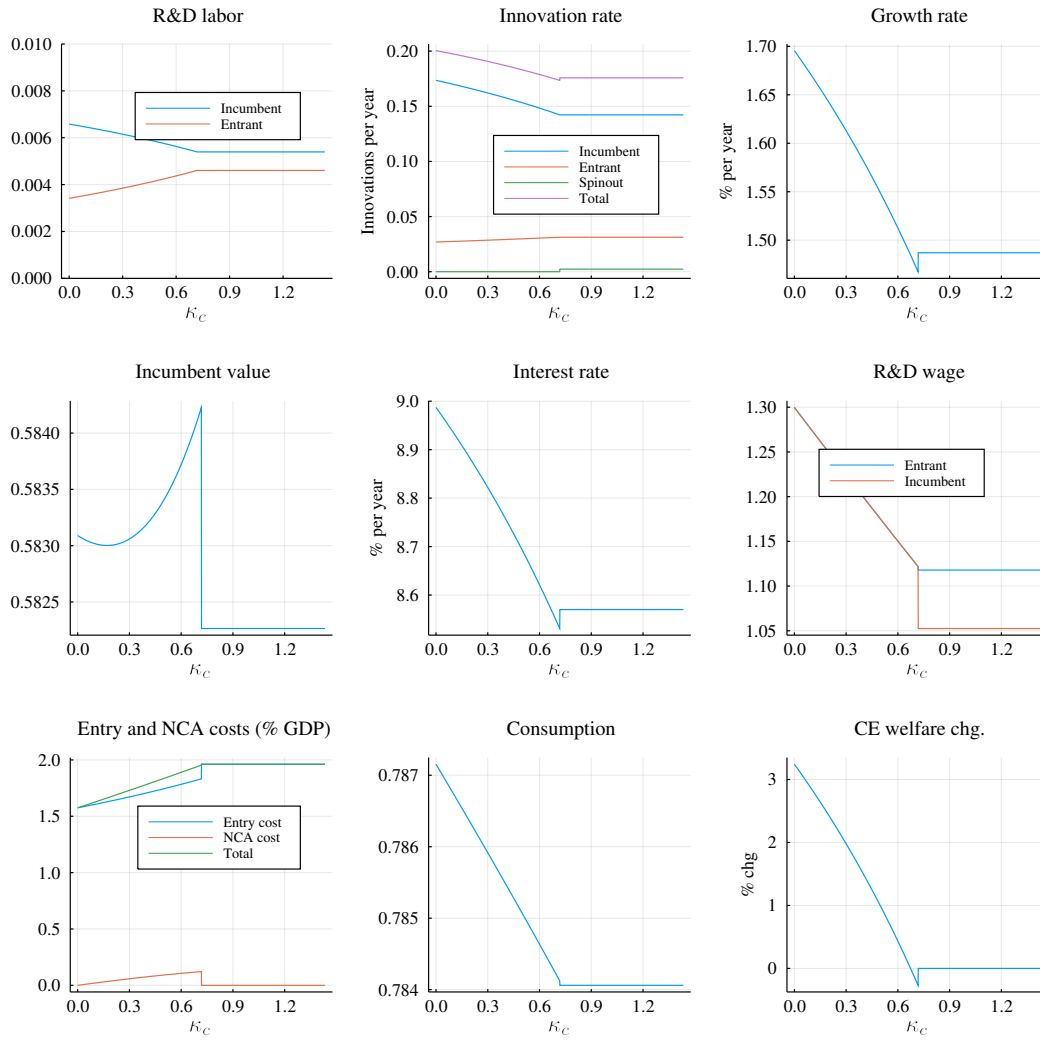


Figure A5: Effect of varying κ_c on equilibrium variables and welfare.

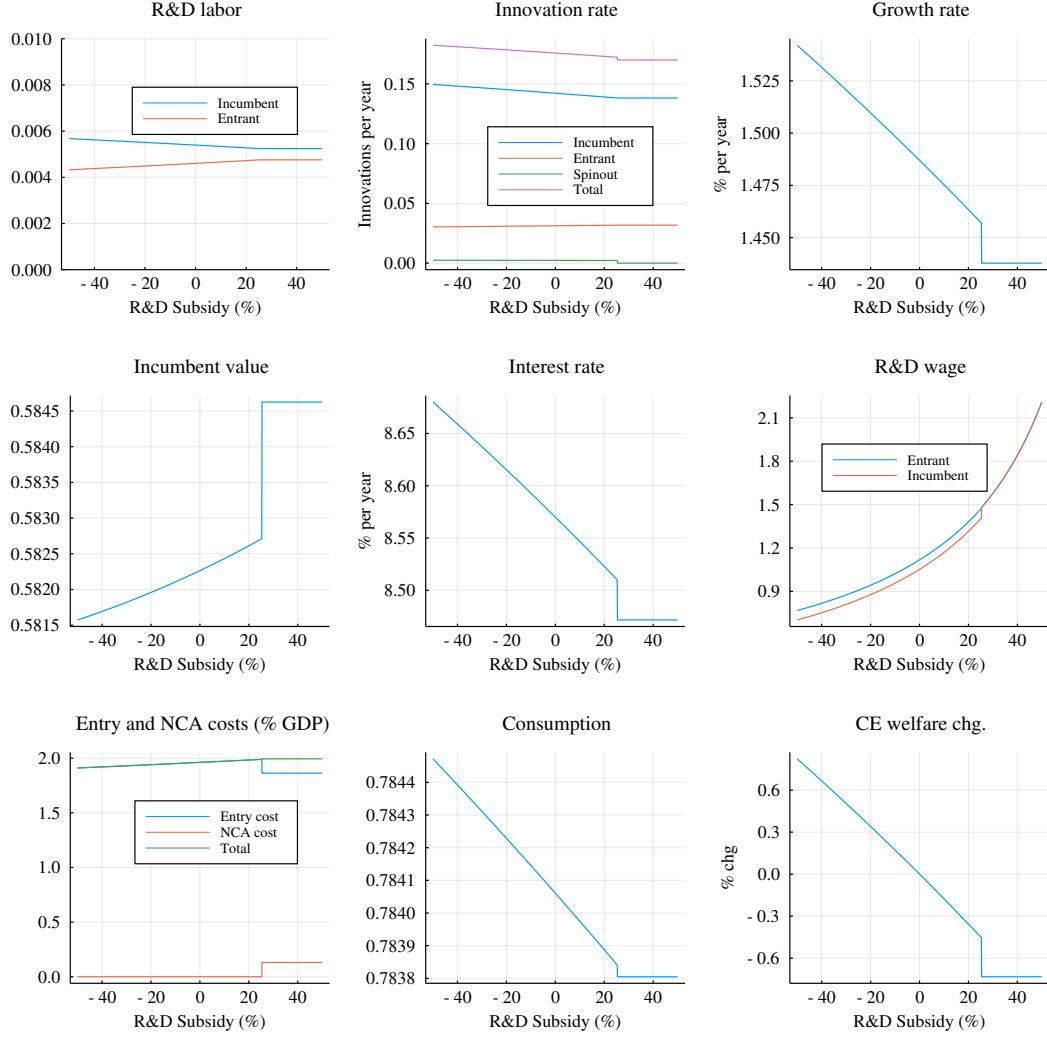


Figure A6: Summary of equilibrium for baseline parameter values and various values of the untargeted R&D subsidy T_{RD} . This assumes that $\kappa_c = 1.1\bar{\kappa}_c$.

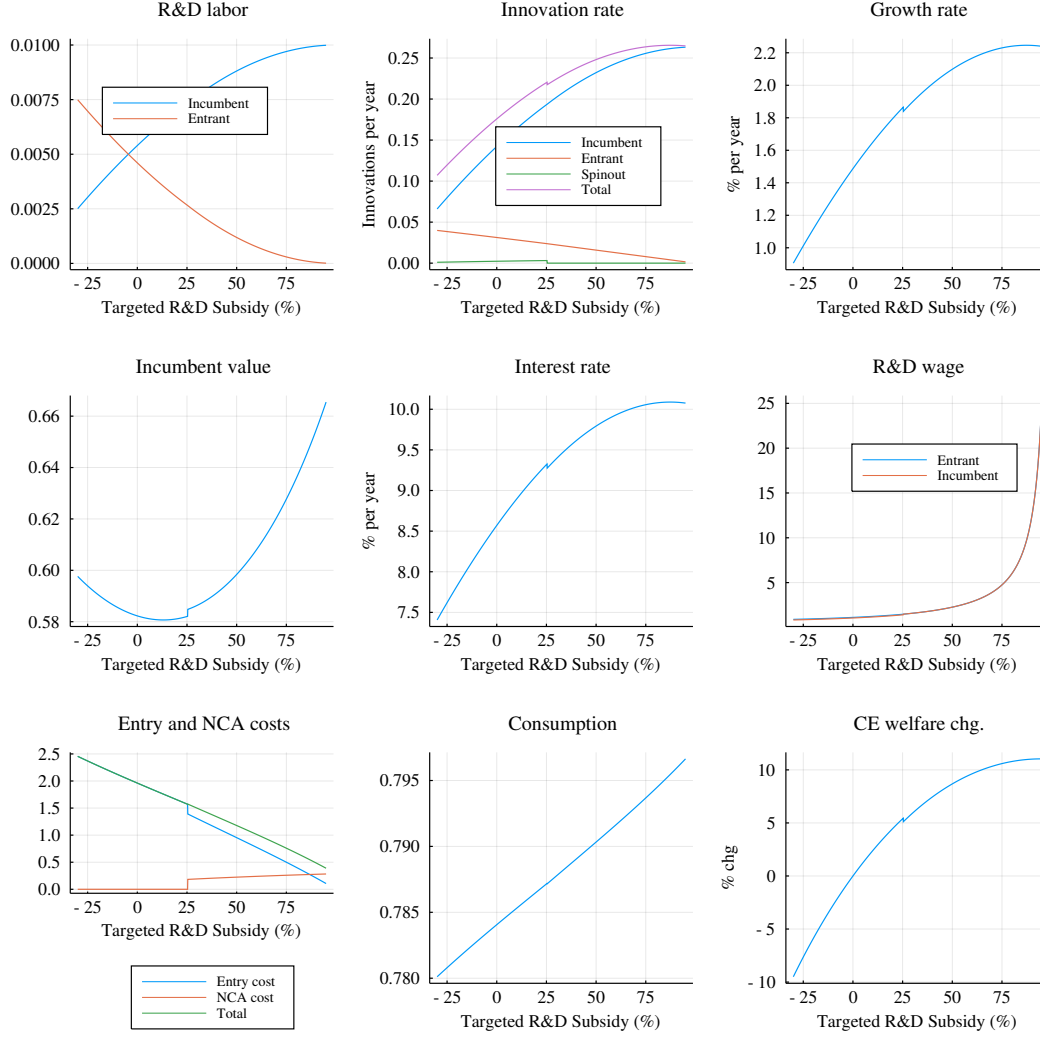


Figure A7: Summary of equilibrium for baseline parameter values and various values of the targeted R&D subsidy $T_{RD,I}$. This assumes that $\kappa_c = 1.1\bar{\kappa}_c$.

2.B Model appendix

2.B.1 Proofs of propositions

Proof of Proposition 2.2.2

Below, I assume that the value of incumbency in line j is differentiable in t conditional on there being no innovations.³⁶

Proof. If $z > 0$ then the FOC holds with equality; otherwise, we can ignore that terms multiplied by z in the incumbent's HJB. Hence, the incumbent HJB implies

$$(r + \hat{\tau})V(j, t|q) - \dot{V}(j, t|q) = \tilde{\pi}q, \quad (2.70)$$

where I used $\hat{\tau}_{jt} = \hat{\tau}$ on a symmetric BGP. This differential equation has a time-independent solution, given by

$$\begin{aligned} V(j, t|q) &= \frac{\tilde{\pi}}{r + \hat{\tau}}q \\ &= \tilde{V}q. \end{aligned} \quad (2.71)$$

The incumbent HJB also has time-dependent solutions. Intuitively, one has to rule out equilibria where the wage to consumption ratio shrinks or grows exponentially proportionally with $V(j, t|q)$. To prove this, first rearrange the time-dependent

³⁶This excludes by assumption equilibria in which there may be stochastic jumps in the value function. To my knowledge, this restriction is standard in treatments of this type of model, such as in the seminal Grossman and Helpman 1991 and Acemoglu 2009.

incumbent HJB to obtain

$$\dot{V}(j, t|q) = (r + \hat{\tau})V(j, t|q) - \tilde{\pi}q. \quad (2.72)$$

Next, differentiate (2.72) to obtain

$$\ddot{V}(j, t|q) = (r + \hat{\tau})\dot{V}(j, t|q). \quad (2.73)$$

This means that if $\dot{V} < 0$ initially, then $\ddot{V} < 0$ initially as well, and similarly if $\dot{V} > 0$ initially then $\ddot{V} > 0$ initially as well. Hence, if in equilibrium $V(j, t|q)$ drifts locally, it must drift monotonically.

Suppose first that $\dot{V}(j, t|q) < 0$. Then (2.73) implies that $\dot{V}(j, t|q)$ tends to $-\tilde{\pi}q$ as $t \rightarrow \infty$. This means that V reaches a negative value in finite time with positive probability. This contradicts optimality since the incumbent is always free to choose $z = 0$ and earn flow profits $\tilde{\pi}q$.

Next, suppose that $\dot{V} > 0$ initially, then

$$\frac{\dot{V}}{V} = r + \hat{\tau} - \frac{\tilde{\pi}q}{V}, \quad (2.74)$$

so V grows at a rate that asymptotically approaches the exponential rate $r + \hat{\tau}$.

Suppose first that $z > 0$. Differentiating the FOC of the incumbent FOC yields

$$-\frac{\dot{V}(j, t|q)}{V(j, t|q)} = g - \frac{\dot{w}_{RD}(t)}{\hat{w}_{RD}(t)}. \quad (2.75)$$

This implies that with positive probability $\hat{w}_{RD}(t)\hat{z} > \tilde{Y}$, which is incompatible with final goods market clearing.

If instead $z = 0$, taking logs and differentiating the entrant optimality condition yields

$$\frac{\dot{V}(j, t|\lambda q)}{V(j, t|\lambda q)} = \frac{\dot{\hat{w}}_{RD}(t)}{\hat{w}_{RD}(t)} - g, \quad (2.76)$$

where I used $\frac{d \log(x)}{dt} = \frac{\dot{x}}{x}$ and $\frac{\dot{Q}_t}{Q_t} = g$. This is the same as (2.75) but evaluated at the quality one step above the frontier quality. It means that if the incumbent value is growing for constant q , the R&D wage must grow faster than the economy. This yields the same contradiction as before. $\square$

Proof of Proposition 2.2.3

Proof. Using the representation $V(j, t|q) = \tilde{V}q$ derived in Proposition 2.2.2 in the incumbent HJB (2.30) and dividing both sides by q yields

$$(r + \hat{\tau})\tilde{V} = \tilde{\pi} + \max_{\substack{\mathbf{1}^{NCA} \in \{0,1\} \\ z \geq 0}} \left\{ z \left(\chi(\lambda - 1)\tilde{V} - w_{RD}(\mathbf{1}^{NCA}) \right. \right. \\ \left. \left. - (1 - \mathbf{1}^{NCA})\nu\tilde{V} - \mathbf{1}^{NCA}\kappa_c\nu\tilde{V} \right) \right\}. \quad (2.77)$$

In any symmetric BGP with $z > 0$, Lemma 2.2.1 determines the relationship between $w_{RD,jt}(\mathbf{1}_{jt}^{NCA})$ and $\hat{w}_{RD,t}$. Substituting in $w_{RD}(\mathbf{1}^{NCA})$ using the indifference condition

(2.25) derived in Lemma 2.2.1 yields

$$\begin{aligned}
(r + \hat{\tau})\tilde{V} = \tilde{\pi} + \max_{\substack{\mathbb{1}^{NCA} \in \{0,1\} \\ z \geq 0}} & \left\{ z \left(\overbrace{\chi(\lambda - 1)\tilde{V}}^{\mathbb{E}[\text{Benefit from R\&D}]} - \hat{w}_{RD} \right. \right. \\
& \left. \left. - \underbrace{(1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu\tilde{V}}_{\text{Net cost from spinout formation}} - \overbrace{\mathbb{1}^{NCA}\kappa_c\nu\tilde{V}}^{\text{Direct cost of NCA}} \right) \right\}.
\end{aligned} \tag{2.78}$$

Let $\bar{\kappa}_c(\kappa_e, \lambda) = 1 - (1 - \kappa_e)\lambda$. If $z > 0$, the incumbent maximizes her flow payoff by choosing $\mathbb{1}^{NCA} \in \{0, 1\}$ which maximizes the term multiplying z . Therefore, $\mathbb{1}^{NCA} = 1$ is strictly preferred iff $1 - (1 - \kappa_e)\lambda > \kappa_c$, which is equation (2.35). $\square$

Proof of Proposition 2.2.4

Proof. First, suppose that Assumption 2 holds. To show existence, guess and verify that $V(j, t|q) = \tilde{V}q$ and solve for equilibrium variables as described in the last section. Assumption 1 guarantees that household utility is finite and the obtained allocation is in fact an equilibrium. To show uniqueness, first notice that in any symmetric BGP, one has $V(j, t|\bar{q}_{jt}) = \tilde{V}\bar{q}_{jt}$ by Proposition 2.2.2 and its corollary. Given this representation and $\kappa_c \neq \bar{\kappa}_c$, Proposition 2.2.3 implies that all symmetric BGPs have $\mathbb{1}_{jt}^{NCA} = \mathbb{1}^{NCA}$ for the same value for $\mathbb{1}^{NCA}$. Using these facts in the equilibrium conditions above one can recursively compute all equilibrium variables.

Now suppose Assumption 2 does not hold. Then $z > 0$ contradicts equilibrium. A symmetric BGP therefore must have $z = 0$. Uniqueness is immediate, since we already know that $\hat{z} = \bar{L}_{RD}$ and $\tau^S = 0$ so we can compute all equilibrium

variables uniquely following the steps in the main text. It remains to confirm that $z = 0$ is in fact optimal for the incumbent. First suppose that the first inequality fails, i.e. the usual steps imply $\hat{z} < 0$. Because $\hat{w}_{RD} > 0$ in any equilibrium, the denominator $\chi(\lambda - 1) - (1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu - \mathbb{1}^{NCA}\kappa_c\nu$ is negative. Inspecting the incumbent's FOC, this condition implies that there is no positive value $\tilde{V}$ such that $z > 0$ satisfies the incumbent's FOC. Therefore, $z = 0$ is consistent with equilibrium. Next, suppose that the usual steps imply $\hat{z} > \bar{L}_{RD}$. Define ξ as the value such that $\hat{w}_{RD}/\tilde{V} = \xi$ implies incumbents are indifferent about R&D. The fact that the expression for $\hat{z}$ implies $\hat{z} > \bar{L}_{RD}$ means that, in order for $\hat{z} = \bar{L}_{RD}$ to be consistent with entrant optimality, the R&D wage to incumbent value ratio must be higher. That is, in equilibrium $\hat{w}_{RD}/\tilde{V} > \xi$. This makes innovation strictly less profitable for the incumbent. Since she would have been indifferent when $\hat{w}_{RD}/\tilde{V} = \xi$, she strictly prefers $z = 0$ when $\hat{w}_{RD}/\tilde{V} > \xi$. This confirms that the constructed equilibrium is in fact an equilibrium. Finally, NCA policy is not determined by optimality because $z = 0$ implies that it is irrelevant to the incumbent's optimization problem; and it has no effect on other equilibrium variables as its only effect is through spinout formation or the noncompete cost, both of which are zero when $z = 0$. $\square$

2.B.2 Additional derivations

Growth accounting equation

Let $\Delta > 0$ and let $J_0(\Delta)$ ($J_1(\Delta)$) denote the indices $j \in [0, 1]$ on which innovation occurs zero (one) times between t and $t + \Delta$. By a law of large numbers applied to the continuum of random processes $\{\tilde{q}_{jt}\}_{j \in [0, 1]}$ (see Uhlig 1996 for more details), the

set $J_1(\Delta)$ has measure $\mu_1\Delta = (\tau + \tau^S + \hat{\tau})\Delta + o(\Delta)$. The set $J_0(\Delta)$ has measure $1 - \mu_1\Delta + o(\Delta)$.

$$\begin{aligned}
Q_{t+\Delta} &= \int_0^1 \bar{q}_{j,t+\Delta} dj = \int_{j \in J_0} \bar{q}_{jt} dj + \int_{j \in J_1} \lambda \bar{q}_{jt} dj + o(\Delta) \\
&= (1 - \mu_1\Delta - o(\Delta))Q_t + (\mu_1\Delta + o(\Delta))\lambda Q_t + o(\Delta) \\
&= (1 - \mu_1\Delta)Q_t + \mu_1\Delta\lambda Q_t + o(\Delta),
\end{aligned} \tag{2.79}$$

where I used the fact that $\mathbb{E}[\bar{q}_{jt}|j \in J_0, t] = \mathbb{E}[\bar{q}_{jt}|j \in J_1, t] = Q_t$, since innovations happen at the same rate regardless of $\bar{q}_{jt}$. It follows that

$$\frac{\dot{Q}_t}{Q_t} = \lim_{\Delta \rightarrow 0} \frac{Q_{t+\Delta} - Q_t}{\Delta} = (\lambda - 1)\mu_1. \tag{2.80}$$

Multiplicity of equilibria

On the knife edge $\kappa_c = \bar{\kappa}_c$, there are multiple equilibria with distinct growth and welfare implications. This results from the fact that a positive mass of incumbents are indifferent about their NCA policy. The first proposition states that there are two symmetric BGPs where all incumbents choose the same policy.

Proposition 2.B.1. *If Assumptions 1 and 2 hold and $\kappa_c = \bar{\kappa}_c$ (as defined in Proposition 2.2.3), then:*

1. *There exist exactly two symmetric BGPs with $\mathbb{1}_{jt}^{NCA} = \mathbb{1}^{NCA}$: one with $\mathbb{1}_{jt}^{NCA} = 0$ and one with $\mathbb{1}_{jt}^{NCA} = 1$.*
2. *Both such equilibria have the same R&D labor allocations $z, \hat{z}$*

3. The equilibrium with $\mathbb{1}_{jt}^{NCA} = 0$ has a higher growth rate g

Proof. The proof of the first part is essentially the same as that of the previous proposition. The only difference is that either choice $\mathbb{1}_{jt}^{NCA} = 1$ or $\mathbb{1}_{jt}^{NCA} = 0$ is valid under Proposition 2.2.3. Given the representation $V(j, t|q) = \tilde{V}q$ and the scaling of wages $\hat{w}_{RD,t} = \hat{w}_{RD}Qt$ and $w_{RD,j}(\mathbb{1}^{NCA}) = w_{RD}D(\mathbb{1}^{NCA})Q_t$, the derivation above uniquely determines uniquely the rest of the equilibrium conditional on x . This equilibrium has finite household utility as long as Assumption 1 holds.

The second part follows from the fact that when $\kappa_c = \bar{\kappa}_c$, the expressions for equilibrium R&D effort $\hat{z}, z$ do not depend on $\mathbb{1}^{NCA}$. The reason is that $\mathbb{1}^{NCA}$ only affects $\hat{z}, z$ through its effect on the incumbent's effective wage, but here is the incumbent is indifferent between $\mathbb{1}^{NCA} = 1$ and $\mathbb{1}^{NCA} = 0$ hence faces the same effective wage. Mathematically, (2.39) has the expression $(1 - \mathbb{1}^{NCA})(1 - (1 - \kappa_e)\lambda)\nu - \mathbb{1}^{NCA}\kappa_c\nu = (1 - \mathbb{1}^{NCA})\bar{\kappa}_c\nu + \mathbb{1}^{NCA}\kappa_c\nu$ in the denominator. Since $\kappa_c = \bar{\kappa}_c$, $\hat{z}$ is unaffected by $\mathbb{1}^{NCA}$, which in turn implies z is also unaffected.

The last statement follows from the fact that $z, \hat{z}$ are the same in both equilibria, but $\tau^S = 0$ when $\mathbb{1}^{NCA} = 1$ and $\tau^S = \nu z^I > 0$ when $\mathbb{1}^{NCA} = 0$. By the growth accounting equation (2.41), this implies g is higher when $\mathbb{1}^{NCA} = 0$. $\square$

The second proposition shows that there is a continuum of symmetric BGPs where a constant fraction of incumbents use NCAs.

Proposition 2.B.2. *If $\theta \geq 1$, $\kappa_c = \bar{\kappa}_c$, and $\left(\frac{\hat{\chi}(1-\kappa_e)\lambda}{\chi(\lambda-1)-\kappa_c\nu}\right)^{1/\psi} < \bar{L}_{RD}$, then for all $f \in (0, 1)$ there exists a symmetric BGP in which, at any given time t , a fraction f of incumbents j have $\mathbb{1}_{jt}^{NCA} = 1$.*

Proof. Consider the generalized growth accounting equation (it simplifies to the one in the main text when $\mathbb{1}_{jt}^{NCA} = \mathbb{1}^{NCA}$),

$$g_t = (\lambda - 1) \left(\tau + \hat{\tau} + z\nu \int_{j:\mathbb{1}_{jt}^{NCA}=0} \frac{\bar{q}_{jt}}{Q_t} dj \right). \quad (2.81)$$

Unless the integral term is constant, then g_t is non-constant, even with constant $z_{jt}, \hat{z}_{jt}$. The integral is equal to the product of the mass m_t^0 of goods whose incumbents choose $\mathbb{1}_{jt}^{NCA} = 0$ and the average relative quality of those goods $\gamma_t^0 = E[\frac{\bar{q}_{jt}}{Q_t} | \mathbb{1}_{jt}^{NCA} = 0]$. Relative to the baseline model, the only substantial modification is that one needs to derive an expression for the evolution over time of

$$\Gamma_t^{\mathbf{x}} = m_t^{\mathbf{x}} \gamma_t^{\mathbf{x}} Q_t, \quad \mathbf{x} \in \{0, 1\}, \quad (2.82)$$

and show that

$$\frac{\dot{\Gamma}_t^0}{\Gamma_t^0} = \frac{\dot{\Gamma}_t^1}{\Gamma_t^1}. \quad (2.83)$$

In this proof I will show that the integral remains constant as long as the random process $\mathbb{1}_{jt}^{NCA}$ follows a certain stationary Markov process with states $\{0, 1\}$. One such Markov process for $\mathbb{1}_{jt}^{NCA}$ is to assume that $\mathbb{1}_{jt}^{NCA}$ resets every time there is a new incumbent. To take the simplest scenario for the sake of exposition, suppose that the transition probabilities do not depend on the state. Specifically, suppose that, conditional on a transition, the likelihood of transitioning to $\mathbb{1}^{NCA} = 1$ is $p \in (0, 1)$.

The equilibrium quantities Γ^0, Γ^1 evolve according to

$$\Gamma_{t+\Delta}^0 = \overbrace{(1 - (\hat{\tau} + \nu z)\Delta)\Gamma_t^0}^{\text{No innovations}} + \overbrace{\tau\Delta(\lambda - 1)\Gamma_t^0}^{\text{Innovating incumbents}} + \overbrace{(1 - p)\lambda\left(\underbrace{(\hat{\tau} + \nu z)\Delta\Gamma_t^0}_{\mathbb{1}_{jt}^{NCA=0}} + \underbrace{\hat{\tau}\Delta\Gamma_t^1}_{\mathbb{1}_{jt}^{NCA=1}}\right)}^{\text{Inflows}} + o(\Delta), \quad (2.84)$$

$$\Gamma_{t+\Delta}^1 = \overbrace{(1 - \hat{\tau}\Delta)\Gamma_t^1}^{\text{No innovations}} + \overbrace{\tau\Delta(\lambda - 1)\Gamma_t^1}^{\text{Innovating incumbents}} + p\lambda\left(\underbrace{(\hat{\tau} + \nu z)\Delta\Gamma_t^0}_{\mathbb{1}_{jt}^{NCA=0}} + \underbrace{\hat{\tau}\Delta\Gamma_t^1}_{\mathbb{1}_{jt}^{NCA=1}}\right) + o(\Delta), \quad (2.85)$$

where $o(\Delta)$ has the usual meaning that $\lim_{\Delta \rightarrow 0} \frac{o(\Delta)}{\Delta} = 0$. Subtracting Γ_t^x , dividing by Δ , and taking the limit as $\Delta \rightarrow 0$ yields

$$\dot{\Gamma}_t^0 = -(\hat{\tau} + \nu z)\Gamma_t^0 + \tau(\lambda - 1)\Gamma_t^0 + (1 - p)\lambda\left((\hat{\tau} + \nu z)\Gamma_t^0 + \hat{\tau}\Gamma_t^1\right), \quad (2.86)$$

$$\dot{\Gamma}_t^1 = -\hat{\tau}\Gamma_t^1 + \tau(\lambda - 1)\Gamma_t^1 + p\lambda\left((\hat{\tau} + \nu z)\Gamma_t^0 + \hat{\tau}\Gamma_t^1\right). \quad (2.87)$$

Dividing by Γ_t^x yields

$$\frac{\dot{\Gamma}_t^0}{\Gamma_t^0} = -(\hat{\tau} + \nu z) + \tau(\lambda - 1) + (1 - p)\lambda\left((\hat{\tau} + \nu z) + \hat{\tau}\frac{\Gamma_t^1}{\Gamma_t^0}\right), \quad (2.88)$$

$$\frac{\dot{\Gamma}_t^1}{\Gamma_t^1} = -\hat{\tau} + \tau(\lambda - 1) + p\lambda\left((\hat{\tau} + \nu z)\left(\frac{\Gamma_t^1}{\Gamma_t^0}\right)^{-1} + \hat{\tau}\right). \quad (2.89)$$

Setting $\frac{\dot{\Gamma}_t^0}{\Gamma_t^0} = \frac{\dot{\Gamma}_t^1}{\Gamma_t^1}$ and multiplying both sides by $\frac{\Gamma_t^1}{\Gamma_t^0}$ yields a quadratic equation in $\frac{\Gamma_t^1}{\Gamma_t^0}$, given by

$$0 = \overbrace{(1 - p)\lambda\hat{\tau}}^a \left(\frac{\Gamma_t^1}{\Gamma_t^0}\right)^2 + \overbrace{\left((1 - p)\lambda(\hat{\tau} + \nu z) - \nu z - p\lambda\hat{\tau}\right)}^b \left(\frac{\Gamma_t^1}{\Gamma_t^0}\right) - \overbrace{p\lambda(\hat{\tau} + \nu z)}^c. \quad (2.90)$$

Using $p \in (0, 1)$ and the facts that $\lambda, \hat{\tau} > 0$ and $\nu, z \geq 0$ yields $-4ac > 0$. Then $\frac{\Gamma_t^1}{\Gamma_t^0} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$ implies that there is always exactly one strictly positive real solution for $\frac{\Gamma_t^0}{\Gamma_t^1}$. To see this, note that of course $b^2 - 4ac > 0$ so the all solutions are real. Then, $-4ac > 0$ implies $\sqrt{b^2 - 4ac} > |b|$. Regardless of whether b is positive or negative, $-b + \sqrt{b^2 - 4ac} > 0$ and $b - \sqrt{b^2 - 4ac} < 0$. The positive root is the equilibrium value of $\frac{\Gamma_t^1}{\Gamma_t^0}$. Using

$$\begin{aligned}
\Gamma_t^1 + \Gamma_t^0 &= \int_{j: \mathbf{1}_{j_t}^{NCA}=1} \bar{q}_{jt} dj + \int_{j: \mathbf{1}_{j_t}^{NCA}=0} \bar{q}_{jt} dj \\
&= \int_0^1 \bar{q}_{jt} dj \\
&= Q_t,
\end{aligned} \tag{2.91}$$

one has a linear system of two equations in two unknowns, Γ_t^1 and Γ_t^0 . Given $\frac{\Gamma_t^0}{Q_t} = \int_{j: \mathbf{1}_{j_t}^{NCA}=0} \frac{\bar{q}_{jt}}{Q_t} dj$, the BGP growth rate is given by (2.81) above. $\square$

2.B.3 Policy analysis derivations

R&D subsidy (tax)

Suppose that the planner subsidizes R&D spending at rate T_{RD} (tax if $T_{RD} < 0$). By the same argument as before, Proposition 2.2.2 holds, so $V(j, t|q) = \tilde{V}q$. Similarly,

Lemma 2.2.4 holds. Therefore, the incumbent value $\tilde{V}$ satisfies

$$(r + \hat{\tau})\tilde{V} = \tilde{\pi} + \max_{\substack{\mathbb{1}^{NCA} \in \{0,1\} \\ z \geq 0}} \left\{ z \left(\overbrace{\chi(\lambda - 1)\tilde{V}}^{\mathbb{E}[\text{Benefit from R\&D}]} - \underbrace{(1 - T_{RD})}_{\text{R\&D Subsidy}} \left(\overbrace{\hat{w}_{RD} - (1 - \mathbb{1}^{NCA})(1 - \kappa_e)\lambda\nu\tilde{V}}^{\text{Incumbent R\&D wage}} \right) \right. \right. \\ \left. \left. - \underbrace{(1 - \mathbb{1}^{NCA})\nu\tilde{V}}_{\text{Net cost from spinout formation}} - \overbrace{\mathbb{1}^{NCA}\kappa_c\nu\tilde{V}}^{\text{Direct cost of NCA}} \right) \right\}. \quad (2.92)$$

Then if $z > 0$, the incumbent's optimal NCA policy is given by

$$x = \begin{cases} 1 & \text{if } \kappa_c < \tilde{\kappa}_c, \\ 0 & \text{if } \kappa_c > \tilde{\kappa}_c, \\ \{0, 1\} & \text{if } \kappa_c = \tilde{\kappa}_c, \end{cases} \quad (2.93)$$

where $\tilde{\kappa}_c = 1 - (1 - T_{RD})(1 - \kappa_e)\lambda$. Assuming $z > 0$, by the same logic as before one can obtain an expression for equilibrium $\hat{z}$,

$$\hat{z} = \left(\frac{\hat{\chi}(1 - \kappa_e)\lambda}{\chi(\lambda - 1) - \nu(\mathbb{1}^{NCA}\kappa_c + (1 - \mathbb{1}^{NCA})(1 - (1 - T_{RD})(1 - \kappa_e)\lambda))} \right)^{1/\psi}. \quad (2.94)$$

The rest of the equilibrium allocation and prices can be computed in the same way as before (including how to account for the possibility of $z = 0$), with the exception that the equilibrium R&D wage is now given by

$$\hat{w}_{RD} = (1 - T_{RD})^{-1} \hat{\chi} \hat{z}^{-\psi} (1 - \kappa_e) \lambda \tilde{V}. \quad (2.95)$$

Targeted R&D subsidy (tax)

Suppose that the planner subsidizes incumbent R&D spending at rate $T_{RD,I}$ (tax if $T_{RD,I} < 0$). By the same argument as before, Proposition 2.2.2 holds, so $V(j, t|q) = \tilde{V}q$. Similarly, Lemma 2.2.4 holds. Therefore, the incumbent's value satisfies

$$(r + \hat{\tau})\tilde{V} = \tilde{\pi} + \max_{\substack{\mathbb{1}^{NCA} \in \{0,1\} \\ z \geq 0}} \left\{ z \left(\overbrace{\chi(\lambda - 1)\tilde{V}}^{\mathbb{E}[\text{Benefit from R\&D}]} - \underbrace{(1 - T_{RD,I})}_{\text{R\&D Subsidy}} \left(\overbrace{\hat{w}_{RD} - (1 - \mathbb{1}^{NCA})(1 - \kappa_e)\lambda\nu\tilde{V}}^{\text{R\&D wage}} \right) \right. \right. \\ \left. \left. - \underbrace{(1 - \mathbb{1}^{NCA})\nu\tilde{V}}_{\text{Net cost from spinout formation}} - \overbrace{x\kappa_c\nu\tilde{V}}^{\text{Direct cost of NCA}} \right) \right\}. \quad (2.96)$$

It can be rearranged to a form analogous to (2.36),

$$(r + \hat{\tau})\tilde{V} = \tilde{\pi} + \max_{\substack{\mathbb{1}^{NCA} \in \{0,1\} \\ z \geq 0}} \left\{ z \left(\overbrace{\chi(\lambda - 1)\tilde{V}}^{\mathbb{E}[\text{Benefit from R\&D}]} - (1 - T_{RD,I})\hat{w}_{RD} \right. \right. \\ \left. \left. - \underbrace{(1 - \mathbb{1}^{NCA})(1 - (1 - T_{RD,I})(1 - \kappa_e)\lambda)\nu\tilde{V}}_{\text{Net cost from spinout formation}} - \overbrace{\mathbb{1}^{NCA}\kappa_c\nu\tilde{V}}^{\text{Direct cost of NCA}} \right) \right\}. \quad (2.97)$$

The noncompete policy is the same as before, with new threshold given by

$$\hat{\kappa}_c = 1 - (1 - T_{RD,I})(1 - \kappa_e)\lambda. \quad (2.98)$$

If $z > 0$, using the same approach as before yields an expression for $\hat{z}$,

$$\hat{z} = \left(\frac{(1 - T_{RD,I})\hat{\chi}(1 - \kappa_e)\lambda}{\chi(\lambda - 1) - \nu(\mathbb{1}^{NCA}\kappa_c + (1 - \mathbb{1}^{NCA})(1 - (1 - T_{RD,I})(1 - \kappa_e)\lambda))} \right)^{1/\psi}. \quad (2.99)$$

The remaining equilibrium conditions are

$$\hat{\tau} = \hat{\chi} \hat{z}^{1-\psi}, \quad (2.100)$$

$$z = \bar{L}_{RD} - \hat{z}, \quad (2.101)$$

$$\tau = \chi z, \quad (2.102)$$

$$\tau^S = (1 - \mathbb{1}^{NCA}) \nu z, \quad (2.103)$$

$$g = (\lambda - 1)(\tau + \tau^S + \hat{\tau}), \quad (2.104)$$

$$r = \theta g + \rho, \quad (2.105)$$

$$\tilde{V} = \frac{\tilde{\pi}}{r + \hat{\tau}}, \quad (2.106)$$

$$\hat{w}_{RD} = \hat{\chi} \hat{z}^{-\psi} (1 - \kappa_e) \lambda \tilde{V}. \quad (2.107)$$

Finally, if $\hat{z}$, as given by (2.99), violates $\hat{z} \leq \bar{L}_{RD}$, then $\hat{z} = \bar{L}_{RD}$ and $z = 0$. The rest of the equilibrium can be derived as is in the baseline case.

2.C Calibration appendix

2.C.1 Computing model moments

Profit to GDP

In the model, this ratio is simple to calculate using the solution to the static equilibrium as $\tilde{\pi}/\tilde{Y}$.

R&D to GDP

In the model, the R&D share is the ratio of the wage paid to R&D workers to GDP.

This is

$$\begin{aligned}
\frac{\text{R\&D wage bill}}{\text{GDP}} &= \frac{w_{RD}z + \hat{w}_{RD}\hat{z}}{\tilde{Y}} \\
&= \frac{\hat{w}_{RD}(z + \hat{z}) + (w_{RD} - \hat{w}_{RD})z}{\tilde{Y}} \\
&= \frac{\hat{w}_{RD}(z + \hat{z}) - (1 - \kappa_e)\lambda\tilde{V}\tau^S}{\tilde{Y}}, \tag{2.108}
\end{aligned}$$

where I used $w_{RD} - \hat{w}_{RD} = -(1 - \mathbf{1}^{NCA})(1 - \kappa_e)\lambda\tilde{V}\nu$ and $\tau^S = (1 - \mathbf{1}^{NCA})\nu z$.

Growth share OI

The model moment that corresponds here is the share of growth due to own innovation by incumbents of age ≥ 6 . In the model, the fraction of OI growth due to incumbents in a given age group is exactly their fraction of employment: innovations arrive at the same rate for each incumbent, and their impact on aggregate growth is proportional to the incumbent's relative quality, which is proportional to employment. Hence old incumbents' share of growth due to own innovation is simply one minus the employment share calculated in the previous paragraph, $e^{((\hat{\tau}_I - 1)g - (\hat{\tau} + (1 - \mathbf{1}^{NCA})z\nu)) \cdot 6}$. Finally, the fraction of aggregate growth due to OI is $\hat{\tau}_i$, defined above. The fraction

of growth due to incumbents of age at least 6 is the product of the two,

$$\begin{aligned} \text{Age } \geq 6 \text{ share of OI} &= \hat{\tau}_I \frac{\ell(6)}{\ell(0)} \\ &= \hat{\tau}_I e^{((\hat{\tau}_I - 1)g - (\hat{\tau} + (1 - \mathbb{1}^{NCA})z\nu)) \cdot 6}. \end{aligned} \quad (2.109)$$

Entry rate

Let $\ell(a)$ denote the density of incumbent employment at age a incumbents. Then $\ell(a)$ is characterized by

$$\ell(a) = \ell(0) e^{((\hat{\tau}_I - 1)g - (\hat{\tau} + \tau^S))a}, \quad (2.110)$$

$$1 - \hat{z} = \int_0^\infty \ell(a) da. \quad (2.111)$$

where $\hat{\tau}_I = \frac{\tau}{\tau + \hat{\tau} + \tau^S}$ is the fraction of innovations that are incumbents' own innovations.

The intuition for this characterization of $\ell(a)$ has two parts. First, because all shocks are *iid* across firms in equilibrium, the law of large numbers applied to each cohort of firms implies that we can consider directly the evolution of the cohort as a whole instead of explicitly analyzing the dynamics each individual firm in the cohort. Second, the employment of a firm is proportional to its relative quality, $l_j \propto \tilde{q}_j = q_j/Q$, as long as it is the leader. When it is no longer the leader, its employment is zero forever. Putting these two together, $\ell(a)$ must decline at exponential rate g due to the increase in Q_t (obsolescence), increase at rate $\hat{\tau}_I g$ due to incumbents own innovations,

and decline at rate $\hat{\tau} + \tau^S$ due to creative destruction.³⁷ Note that the employment density is strictly decreasing in a . This is because there are no adjustment costs: firms achieve their optimal scale immediately upon entry, and subsequently become obsolete (on average) or lose the innovation race to an entrant. Finally, due to the constant exponential decay of $\ell(a)$, the share of incumbent employment in incumbents of strictly less than 6 years of age is given by

$$\begin{aligned}\Xi_{[0,6)} &= 1 - \frac{\ell(6)}{\ell(0)} \\ &= 1 - e^{((\hat{\tau}_I - 1)g - (\hat{\tau} + \tau^S)) \cdot 6}.\end{aligned}\tag{2.112}$$

To calculate the share of employment in incumbents age < 6 , I use as denominator the employment of intermediate goods firms in the economy (including R&D by entrants). When bringing this to the data, it is equivalent to assuming that the age-employment distribution of final goods firms is the same as that of intermediate goods firms. Using this approach, the share of overall employment in incumbents of age < 6 , including R&D performed by non-producing entrants, is equal to the previously calculated $\Xi_{[0,6)}$ multiplied by the share of total labor in incumbents $1 - L_F - \hat{z}$, added to the R&D labor used by entrants $\hat{z}$, divided by the share of total employment in intermediates $1 - L_F$, and finally multiplied by $2/3$ which is the share

³⁷The second equation imposes consistency with aggregate employment; it implies $\ell(0) = -((\hat{\tau}_I - 1)g - (\hat{\tau} + \tau^S))(1 - \hat{z})$. The calibration does not require this explicit calculation since it is based only on employment shares.

of creative destruction that corresponds to new firms in the data.³⁸ This yields

$$\text{Age} < 6 \text{ share of employment} = \frac{2}{3} \frac{(\Xi_{[0,6)}(1 - L_F - \hat{z}) + \hat{z})}{1 - L_F}. \quad (2.114)$$

The factor 2/3 deserves some additional discussion. According to Klenow and Li 2020, creative destruction by incumbents is responsible for half as much growth as creative destruction by entrants. In this interpretation of the model, both types of creative destruction use the same technology. Therefore, it follows that 2/3 of employment in young firms in the model represents employment in young firms in the data.

Employment share of WSOs

Because successfully innovating spinouts and entrants have identical expected growth dynamics, the BGP share of employment in firms started as spinouts is their share of new incumbents $\frac{\tau^S}{\tau^S + (\frac{2}{3})\hat{\tau}}$, multiplied by the employment share of incumbents $\frac{1 - L_F - (\frac{2}{3})\hat{z}}{1 - L_F}$,

$$\text{Spinout employment share} = \frac{\tau^S}{\tau^S + \frac{2}{3}\hat{\tau}} \times \frac{1 - L_F - (\frac{2}{3})\hat{z}}{1 - L_F}. \quad (2.115)$$

Again, the factor 2/3 reflects the fact that I assume 2/3 of the entrants in the model are new firms in the data.

³⁸Alternatively, one could assume that final goods firms have the same employment-age distribution as other intermediate goods firms. Then the formula would be

$$\text{Age} < 6 \text{ share of employment} = \frac{2}{3} (\Xi_{[0,6)}(1 - \hat{z}) + \hat{z}). \quad (2.113)$$

This has only minor effects on the inferred parameters.

Table D1: Effect of reduction in κ_c on growth, level of consumption, and welfare

Measure	Variable	$\kappa_c > \bar{\kappa}_c$	$\kappa_c = 0$	Chg.
Growth	g	1.487%	1.695%	0.21 p.p.
Level	$\tilde{C}$	0.80	0.80	0%
Welfare	$\tilde{W}$			2.86% (CE)

2.D Policy analysis robustness appendix

2.D.1 NCA cost κ_c

Entry costs as transfers

Table D1 shows the effect on growth, the level of consumption, and welfare of setting $\kappa_c = 0$, treating the costs of entry as transfers to the competitive financial intermediary. The growth effect is the same as in Table 2.3, but the level of consumption is unaffected. This is because the aggregate cost of NCA enforcement is zero both when $\kappa_c = 0$ and when $\kappa_c > \bar{\kappa}_c$, as in the latter case NCAs are prohibitively expensive and not used in equilibrium. The result is that welfare increases due to the increased growth, albeit less as there are entry cost savings from reduced creative destruction. Figure D8 plots the determinants of the growth rate and level of consumption for $\kappa_c \in [0, 2\bar{\kappa}_c]$. For $0 < \kappa_c < \bar{\kappa}_c$, the aggregate direct cost of NCAs is positive. Still, the overall magnitude is quite small, reducing the level of consumption by at most 0.2 percentage points.

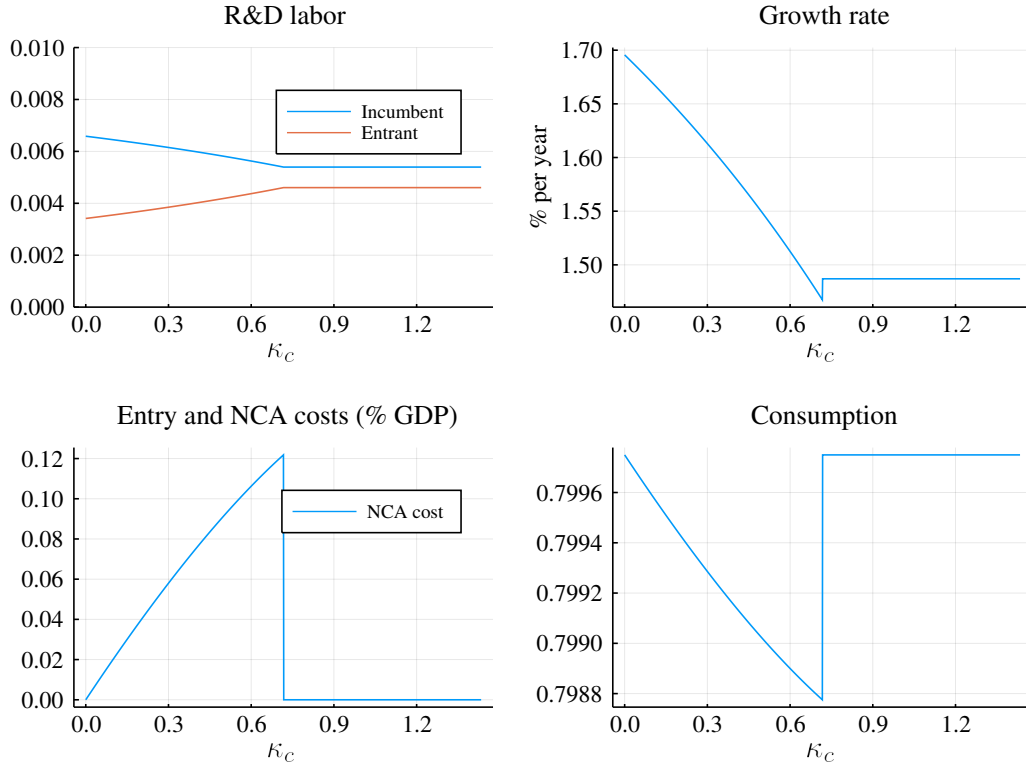


Figure D8: Effect of varying κ_c on key equilibrium variables, considering the entry cost as a transfer to the financial intermediary. The top-left panel shows R&D labor allocated to incumbents (own-product innovation) and entrants (creative destruction). The top-right panel shows the aggregate productivity growth rate. The bottom-left panel shows the direct cost of NCAs. Finally, the bottom-right panel shows the level of consumption.

Incumbent decreasing returns to scale in innovation

As discussed in Section 2.4.2, the magnitude of the increase in growth and welfare would be smaller if the price-elasticity of incumbent demand for R&D labor were lower. In the baseline model, this elasticity is infinite as the incumbent has constant returns to scale. In this section I consider an extended model which specifies the innovation production functions as

$$\tau_{jt} = \chi z_{jt}^{1-\psi}, \quad (2.116)$$

$$\tau_{jt}^S = (1 - \mathbb{1}_{jt}^{NCA}) \nu z_{jt}, \quad (2.117)$$

$$\hat{\tau}_{jt} = \hat{\chi} \hat{z}_{jt}^{1-\hat{\psi}}, \quad (2.118)$$

where I now use the notation $\hat{\psi}$ to refer to the parameter corresponding to ψ in the baseline model, in order to have consistent notation (hats always refer to entrants). Note that I keep the rate of spinout formation linear in z_{jt} . This is necessary for tractability as otherwise the wage paid by the incumbent would depend on z_{jt} : specifically, a higher z_{jt} would imply a lower value of future spinouts per worker and hence require a higher wage.

Equilibrium conditions The equilibrium conditions of this model are the same as before except for the incumbent HJB.³⁹ In particular, note that the use of NCAs in equilibrium again follows (2.35) so it can be derived in closed form. In normalized

³⁹I have not proven uniqueness of the symmetric BGP in this case; however, numerically there is no evidence so far of multiplicity.

terms (i.e., $V(j, t|\bar{q}_{jt}) = \tilde{V}\bar{q}_{jt}$), the incumbent HJB is

$$(r + \hat{\tau})\tilde{V} = \tilde{\pi} + \max_{\substack{z \geq 0 \\ \mathbb{1}^{NCA} \in \{0,1\}}} \left\{ \chi z^{1-\psi}(\lambda - 1)\tilde{V} - zw_{RD}(\mathbb{1}^{NCA}) \right. \\ \left. - (1 - \mathbb{1}^{NCA})z\nu\tilde{V} - \mathbb{1}^{NCA}z\kappa_c\nu\tilde{V} \right\}. \quad (2.119)$$

The first order condition with respect to z is given by

$$(1 - \psi)\chi z^{-\psi}(\lambda - 1)\tilde{V} = w_{RD}(\mathbb{1}^{NCA}) + (1 - \mathbb{1}^{NCA})\nu\tilde{V} - \mathbb{1}^{NCA}\kappa_c\nu\tilde{V}, \quad (2.120)$$

which yields an expression for $z(\tilde{V}, w_{RD}(\mathbb{1}^{NCA}), \mathbb{1}^{NCA})$,

$$z(\tilde{V}, w_{RD}(\mathbb{1}^{NCA}), \mathbb{1}^{NCA}) = \left(\frac{(1 - \psi)\chi(\lambda - 1)\tilde{V}}{w_{RD}(\mathbb{1}^{NCA}) + (1 - \mathbb{1}^{NCA})\nu\tilde{V} - \mathbb{1}^{NCA}\kappa_c\nu\tilde{V}} \right)^{\frac{1}{\psi}}. \quad (2.121)$$

Plugging (2.121) into the incumbent HJB yields an equilibrium relationship between $\tilde{V}$, $w_{RD}(\mathbb{1}^{NCA})$ (given $r, \hat{\tau}, \tilde{\pi}, \mathbb{1}^{NCA}$ in the background). Suppressing the dependence of w_{RD} on $\mathbb{1}^{NCA}$ for clarity, this is

$$(r + \hat{\tau})\tilde{V} = \tilde{\pi} + \chi z(\tilde{V}, w_{RD}, \mathbb{1}^{NCA})^{1-\psi}(\lambda - 1)\tilde{V} \\ - z(\tilde{V}, w_{RD}, \mathbb{1}^{NCA})(w_{RD} + (1 - \mathbb{1}^{NCA})\nu\tilde{V} - \mathbb{1}^{NCA}\kappa_c\nu\tilde{V}). \quad (2.122)$$

Solution algorithm I use the following algorithm to compute a symmetric BGP.

1. Use (2.35) to determine $\mathbb{1}^{NCA}$.

2. Guess $r, \hat{\tau}$.
3. Use nonlinear root finding algorithm to compute $\tilde{V}, w_{RD}(\mathbf{1}^{NCA}), \hat{w}_{RD}, z, \hat{z}$ by simultaneously solving (2.122), entrant optimization, worker indifference condition for R&D labor supply, and R&D labor market clearing.
4. Compute $\tau, \hat{\tau}, \tau^S$ and $g = (\lambda - 1)(\tau + \hat{\tau} + \tau^S)$.
5. Compute $r = \theta g + \rho$ (Euler equation).
6. Check whether $r, \hat{\tau}$ are within tolerance of guesses from Step 2. If so, an equilibrium has been found. If not, update and return to Step 2.

Results To study the properties of this model, I recalibrate to the same target moments. I assume $\psi = 0.5$ which is a standard choice in the literature. As discussed in Akcigit and Kerr 2018, this value of ψ is consistent with the price-elasticity of R&D that has been found in the micro data. The calibration again is able to match the moments exactly. The inferred parameters, however, are different than in the model with a constant returns to scale production function. They are listed in Table D2.

Table D3 shows the results of reducing κ_c to zero in this model. Growth increases by 0.18 percentage points and welfare increases by 2.65% in CE terms. This is slightly weaker than the results in the case with constant returns to scale. Table D4 decomposes the sources of growth in the high and low κ_c BGPs. As in the baseline model, $\kappa_c = 0$ has a higher allocation of R&D to own-product innovation. This increase growth for the same reason as in the baseline case. Figure D9 traces these effects for all values of κ_c between $\bar{\kappa}_c$ and zero.

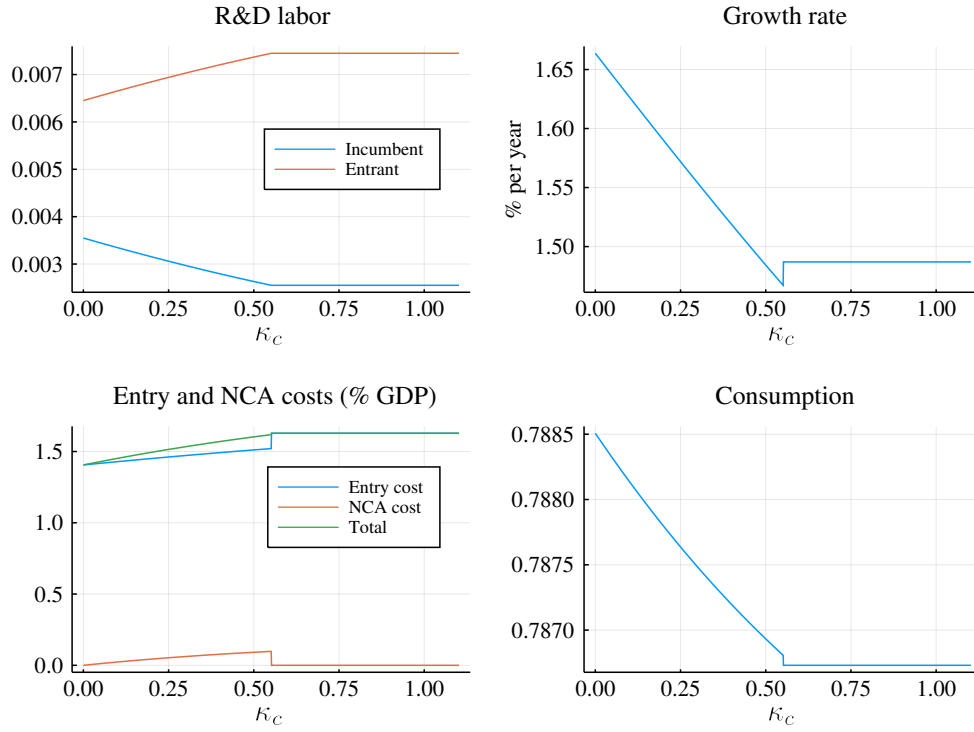


Figure D9: Effect of varying κ_c on key equilibrium variables in the model with incumbent decreasing returns to scale in innovation. The top-left panel shows R&D labor allocated to incumbents (own-product innovation) and entrants (creative destruction). The top-right panel shows the aggregate productivity growth rate. The bottom-left panel shows the direct cost of NCAs. The bottom-right panel shows the level of consumption.

Table D2: Calibrated parameters with DRS incumbent innovation

Parameter	Value	Description	Source
θ	2	$\theta^{-1} = \text{IES}$	External
ψ	0.5	Incumbent R&D curvature	External
$\hat{\psi}$	0.5	Entrant R&D curvature	External
ρ	0.0559	Discount rate	Internal
β	0.094	$\beta^{-1} = \text{EoS intermediate goods}$	Internal
λ	1.087	Quality ladder step size	Internal
χ	2.73	Incumbent R&D productivity	Internal
$\hat{\chi}$	0.356	Entrant R&D productivity	Internal
κ_e	0.587	Non-R&D entry cost	Internal
ν	0.900	Spinout generation rate	Internal
$\bar{L}_{RD}$	0.01	R&D labor allocation	Internal

Table D3: Effect of reducing κ_c in DRS incumbent innovation calibration

Measure	Variable	$\kappa_c > \bar{\kappa}_c$	$\kappa_c = 0$	Chg.
Growth	g	1.487%	1.664%	0.177 p.p.
Level	$\tilde{C}$	0.786	0.788	0.25%
Welfare	$\tilde{W}$			2.65% (CE)

Variation in target moments

Figure D10 shows the sensitivity of the welfare comparison the moments targeted, including the externally calibrated parameters as pseudo-moments as before. As discussed in the main text, it is computed as $\nabla_{\log m} \tilde{W}|_{\log m} = (J^{-1})^T \nabla_{\log p} W|_{\log p}$, where J is the Jacobian of the mapping from log parameters to moments (so that J^{-1} is the Jacobian of the inverse mapping), and W is the mapping from log parameters the consumption-equivalent percent change in welfare from reducing κ_c from $\kappa_c > \bar{\kappa}_c$ to $\kappa_c = 0$. That is, it is the gradient of the change in welfare to the log change in

Table D4: Decomposition of effect of reducing κ_c on growth and R&D in DRS incumbent innovation calibration

Measure	Variable	$\kappa_c > \bar{\kappa}_c$	$\kappa_c = 0$	Chg.
Growth	g	1.487%	1.664%	0.177 p.p.
incumbents	$(\lambda - 1)\tau$	1.20%	1.41%	0.21 p.p.
entrants	$(\lambda - 1)\hat{\tau}$	0.268%	0.249%	-0.019 p.p.
spinouts	$(\lambda - 1)\tau^S$	0.020%	0%	-0.02 p.p.
R&D				
incumbents (%)	$z/\bar{L}_{RD}$	25.51%	35.49%	9.98 p.p.
entrants (%)	$\hat{z}/\bar{L}_{RD}$	74.49%	64.51%	-9.98 p.p.

target moments or uncalibrated parameters, taking as given the change in parameters required to continue matching the target moments. For reference, $\nabla_p W|_p$ for each definition of W can be found in Figure A4.

To get a sense of what this means about robustness of the results, suppose that the log of each moment is assumed to have a standard deviation of σ and that this uncertainty is uncorrelated across moments. The uncertainty propagates such that the standard deviation of the CE welfare change is the square root of $(\nabla_m \tilde{W}|_m)^T \Sigma_m \nabla_m \tilde{W}|_m$, where $\Sigma_m = \sigma^2 I_{9 \times 9}$. In this examples this yields 13.2σ standard deviation of the welfare improvement, measured in percentage points. Given a baseline welfare improvement of 3.24%, a standard deviation excludes zero for $\sigma \leq .245$ or about 21.5%. Two standard deviations exclude zero for $\sigma \leq .123$ or about 11.6%.

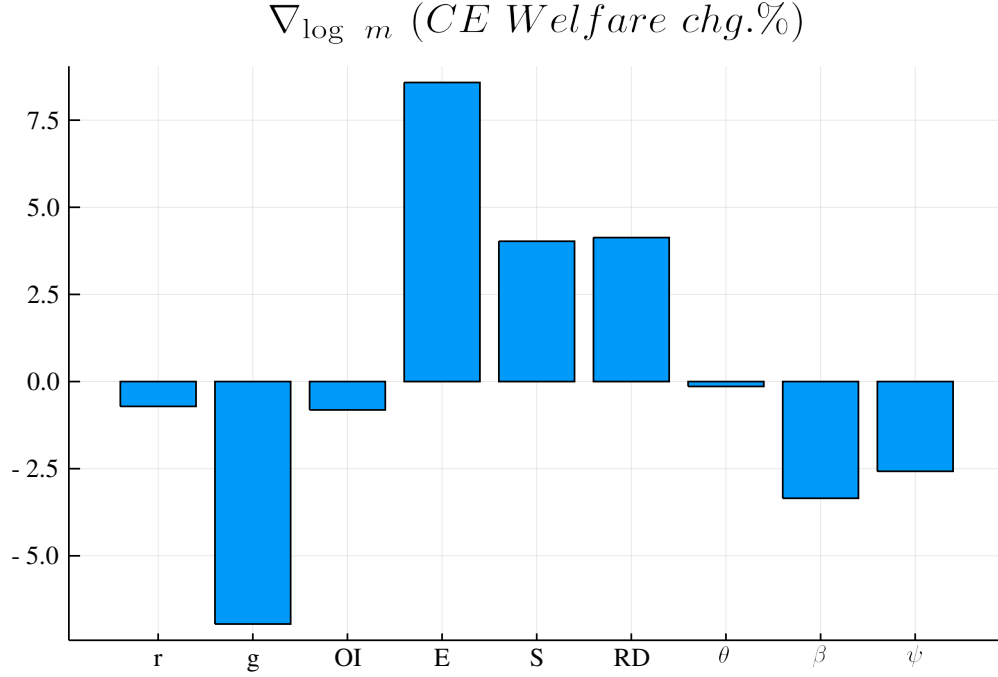


Figure D10: Sensitivity of welfare comparison to moments. This is $(J^{-1})^T \nabla_p W$, where $W(p)$ maps log parameters to the log of the percentage change in BGP consumption which is equivalent to the change in welfare from changing κ_c from ∞ to 0 (i.e. going from banning to frictionlessly enforcing NCAs).

When is $\kappa_c = 0$ bad for welfare?

The sensitivity of the welfare improvement to the entry rate shown in Figure D10 suggests that a calibration targeting a lower entry rate – but, crucially, with the same share of growth coming from young firms – could have the opposite result. Figure D11 shows the analogue of Figure A5 if entry rate targeted is 5% instead of 13.34%. The model is again able to match the moments exactly; inferred parameter values are shown in Table D5. In this low entry calibration, growth and welfare fall when κ_C is reduced to zero. The lower employment in young firms (while holding constant

Table D5: Low entry rate calibration

Parameter	Value	Description	Source
θ	2	$\theta^{-1} = \text{IES}$	External
ψ	0.5	Entrant R&D curvature	External
ρ	0.0559	Discount rate	Internal
β	0.094	$\beta^{-1} = \text{EoS intermediate goods}$	Internal
λ	1.56	Quality ladder step size	Internal
χ	2.77	Incumbent R&D productivity	Internal
$\hat{\chi}$	0.131	Entrant R&D productivity	Internal
κ_e	0.577	Non-R&D entry cost	Internal
ν	0.082	Spinout generation rate	
$\bar{L}_{RD}$	0.01	R&D labor allocation	Internal

Table D6: Effect of reducing κ_c in low entry calibration

Measure	Variable	$\kappa_c > \bar{\kappa}_c$	$\kappa_c = 0$	Chg.
Growth	g	1.487%	1.466%	−0.021 p.p.
Level	$\tilde{C}$	0.793	0.794	0.13%
Welfare	$\tilde{W}$			−0.23% (CE)

the fraction of growth coming from old firms) means that each entry by a young firm must have a higher effect on growth in order for the model to match the growth rate. Furthermore, as shown in Figure A4, the increase in λ eliminates the overall welfare gain from reducing κ_c . As discussed previously, a higher value of λ brings (2.58) closer to unity, weakening the growth increase from reallocation of R&D to own-product innovation.

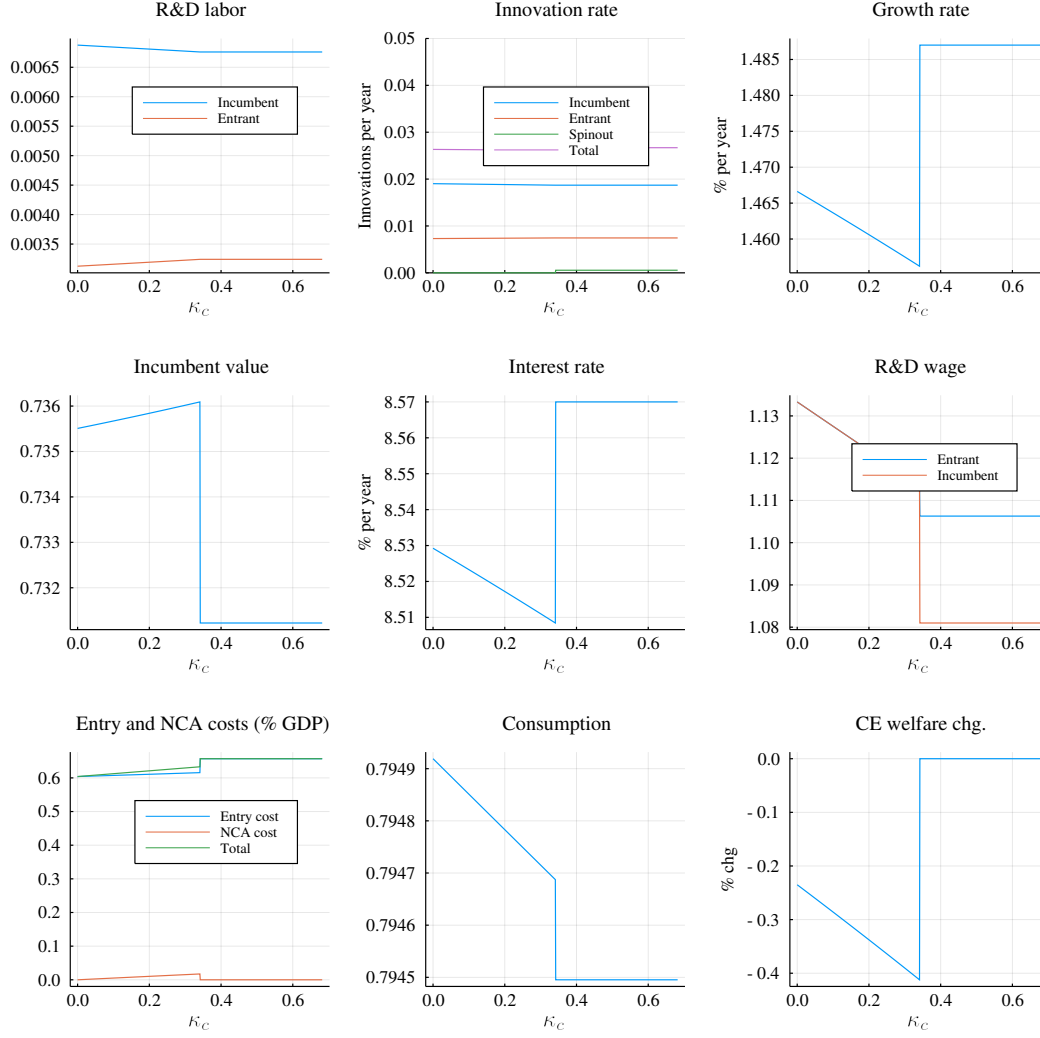


Figure D11: Effect of varying κ_c on equilibrium objects when the model is calibrated to a 5% share of employment in young firms instead of 13.34% as in the baseline calibration.

Table D7: Decomposition of effect of reducing κ_c on growth and R&D in low entry calibration

Measure	Variable	$\kappa_c > \bar{\kappa}_c$	$\kappa_c = 0$	Chg.
Growth	g	1.487%	1.466%	−0.021 p.p.
incumbents	$(\lambda - 1)\tau$	1.04%	1.06%	0.02 p.p.
entrants	$(\lambda - 1)\hat{\tau}$	0.415%	0.407%	−0.008 p.p.
spinouts	$(\lambda - 1)\tau^S$	0.03%	0%	−0.03 p.p.
R&D				
incumbents (%)	$z/\bar{L}_{RD}$	67.6%	68.8%	1.2 p.p.
entrants (%)	$\hat{z}/\bar{L}_{RD}$	32.4%	31.2%	−1.2 p.p.

2.D.2 NCA cost κ_c and targeted R&D subsidy

Entry costs as transfers

Here, I again consider how the result is changed when entry costs are interpreted as transfers to the financial intermediary. The analogue of Figure 2.5 is shown in Figure D12. The optimal welfare improvement is now approximately 10.1%, which is smaller as there is no longer a welfare improvement from a reduction in a resource cost associated with creative destruction. For targeted R&D subsidies above 62%, it is optimal to ban NCAs, compared to a threshold of 77% subsidies in the baseline interpretation of entry costs. The reason is that creative destruction is relatively less inefficient as some of its costs are transfers rather than scarce resource costs. This means that a smaller reallocation of R&D achieves the social optimum and that sacrificing entry by spinouts entails a larger social cost.

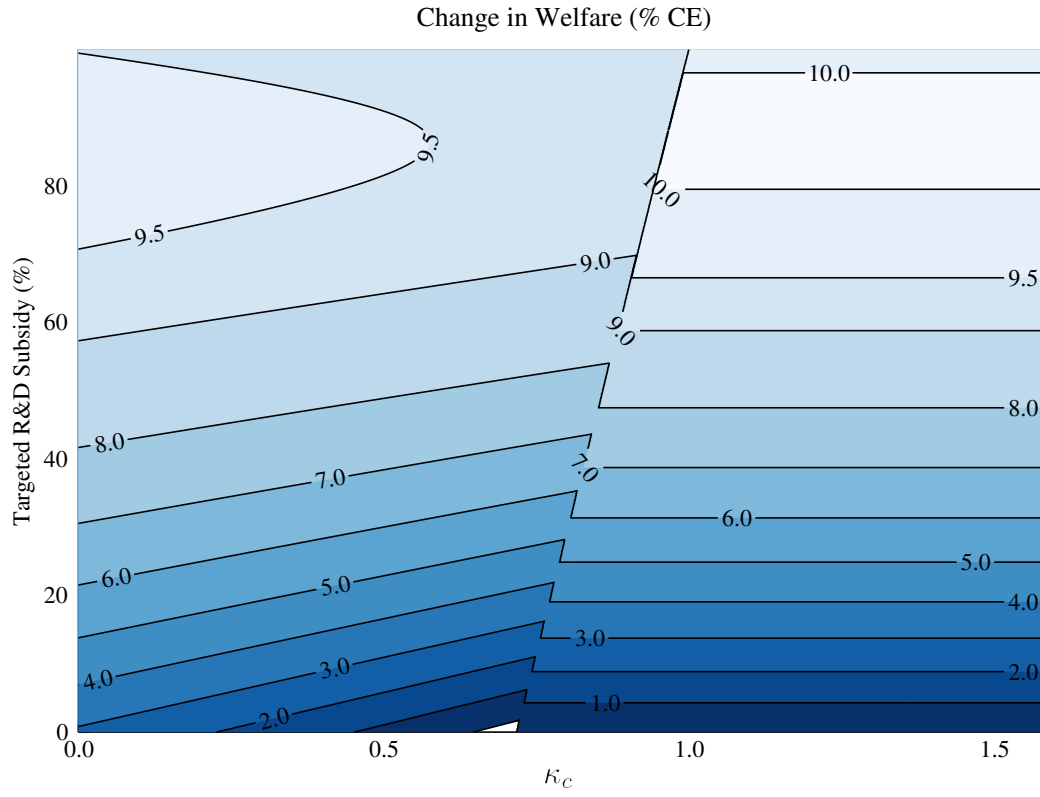


Figure D12: Summary of equilibrium for baseline parameter values and various values of $T_{RD,I}$ and κ_c , considering entry costs as transfers.

Chapter 3

The Latin American Growth Shortfall: Productivity and Inequality¹

3.1 Introduction

The countries of Latin America and the Caribbean (LAC) have experienced poor economic performance for a long time, interrupted only by brief periods of unsustained rapid growth. This paper examines the contribution of improvements in productivity measured by the growth rate of total factor productivity (TFP). It analyzes LAC economic performance by decomposing per capita growth in gross domestic product

¹This chapter is coauthored with Eduardo Fernández-Arias. It is under revision under the same title for the 2021 Latin America and the Caribbean United Nations Regional Human Development Report. We acknowledge valuable feedback from participants at the March 2020 UN Regional Human Development Report conference.

(GDP) into two terms: the estimated growth contribution of factor accumulation per capita (including both physical and human capital) and the productivity improvement in the use of the factors of production in place (growth of TFP). It is important to highlight that this is an accounting decomposition of growth sources and therefore descriptive in nature rather than a causal attribution of the ultimate drivers of output growth. As is customary in growth accounting, the growth of TFP is obtained as a residual accounting for the observed growth in output per worker beyond the estimated direct contribution of factor accumulation, in turn inferred from a production function. In this decomposition, TFP growth reflects both technology-related advances not embodied in capital investments as well as changes in public sector activity and market conditions that affect the aggregate efficiency with which the factors of production available in the economy are utilized.

This analysis demonstrates that a look at the experience through the lens of productivity growth, as opposed to factor accumulation, holds the key to understanding LAC underperformance and, further, that this distinction informs productive development policies. For example, while the promotion of more rapid factor accumulation is typically a costly process involving the diversion of resources to investment, improvements in productivity may be “simply” produced by better, sounder policies and institutions involving little if any economic cost. That low productivity growth is the weak link in observed underperformance would be a reason for optimism regarding LAC’s future economic development. However, failing productivity may also reflect entrenched dysfunctional political economy features

that are highly resistant to change, which would be a reason for pessimism, at least in the short term. It is thus critical to identify the drivers of low productivity growth.

The remainder of the chapter is organized as follows. Section 3.2 (LAC Economic Performance) characterizes the economic performance of LAC over time and shows that the evolution of productivity growth is the main driver of the growth dynamics of the region's output per capita. Section 3.3 (LAC Performance Gaps) gauges LAC performance, comparing it with extra-regional benchmarks and documenting that lower growth has led to a decline in relative output per capita with respect to both developing country peers and the developed countries it aspires to catch up to. In particular, it finds that lower productivity growth is the key factor underlying underperformance. Section 3.4 (LAC Performance in Panel Regressions) formalizes the previous comparative approach within a regression framework to assess statistically the growth gaps of LAC and LAC countries over time. Section 3.5 (Productivity Growth and Inequality) extends the regression framework to look empirically at the connection between economic underperformance and inequality, exploring the hypothesis that low productivity growth and high inequality, two salient characteristics of the region, are linked. Section 3.6 concludes.

3.2 LAC Economic Performance

Per capita output growth in LAC has been remarkably unstable over recent decades. Figure 3.1 summarizes the situation by looking at real per capita GDP annual growth over 1962-2017, representing the region by a simple average over the 16 countries

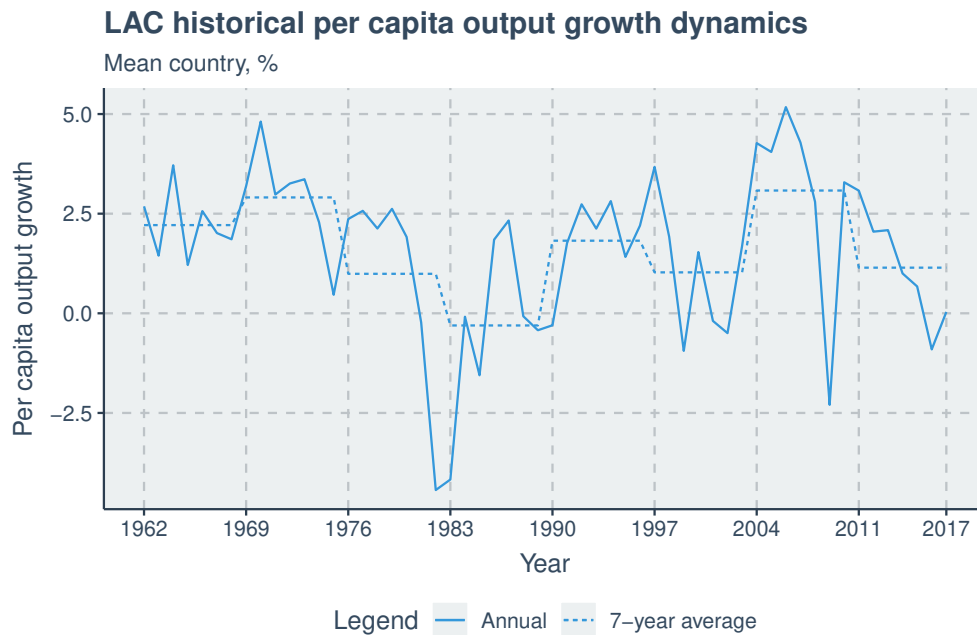


Figure 3.1: Historical mean output growth in Latin America and the Caribbean.

on which complete data are available.² At the yearly frequency, it clearly shows the growth collapse of the LAC debt crisis of the 1980s, starting in earnest in 1983, and, to a lesser extent, the brief growth collapse of 2009 associated with the global Great Recession.

Growth rates at yearly frequencies may fail to be informative on the structural characteristics and trends this paper is set to analyze because they are contaminated by business cycle fluctuations. To control for the business cycle in a parsimonious

²LAC countries are Argentina, Barbados, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Jamaica, Mexico, Peru, Trinidad and Tobago, Uruguay and Venezuela. A balanced panel was considered, neglecting LAC countries with shorter time series for the relevant variables, to allow for simple and robust statistical analysis. Data are taken from Penn World Table (database, version 9.10), Groningen Growth and Development Centre, Faculty of Economics and Business, University of Groningen, Groningen, the Netherlands, <https://www.rug.nl/ggdc/productivity/pwt/>. See the Statistical Appendix for details.

manner in what follows, we consider average annual growth rates over periods of seven years (1962-1968, 1969-1975, 1976-1982, 1983-1989, 1990-1996, 1997-2003, 2004-2010, 2011-2017).³ This periodization also has the advantage of conforming a balanced panel of four periods around the year 1990, which is often regarded as pivotal because it is associated with the start of a new era of market reforms and macroeconomic prudence in the region after the debt crisis.

Filtering business cycle noise by taking 7-year averages in this way, the trend line in Figure 3.1 still shows substantial instability in per capita output growth within a band of about 0 percent to 3 percent per annum. By and large, there are two main growth phases: before and after 1990. Growth before 1990 appears to be reasonably strong at the beginning in the first two periods, but falters in the late 1970s and collapses in the 1980s during the debt crisis. Growth after 1990 recovered and has been sustained but, overall, has not reached the levels of the 1960s and early 1970s. (A more in-depth analysis in the next section will shed light on this issue and show that progress after 1990 has been effectively more successful than appears in Figure 3.1.)

The growth patterns depicted in Figure 3.1 can also be observed by considering the median LAC country (instead of the mean country, Figure 3.2) and, by and large, each of the 16 countries (Figure 3.3). The main exceptions were Chile, Colombia and, to some extent, Uruguay, which appear to have escaped the growth collapse of the debt crisis (while, in countries such as Costa Rica and Jamaica, the crisis materialized a bit earlier and, in countries such as Brazil and Barbados, it came immediately

³Alternatively, a filter can be used to estimate an estimated trend, as in Loayza et al. 2005 or Daude and Fernández-Arias 2010. The qualitative results are similar. Here, this simpler method is used to gain comparability with the regression analysis in the subsequent sections.

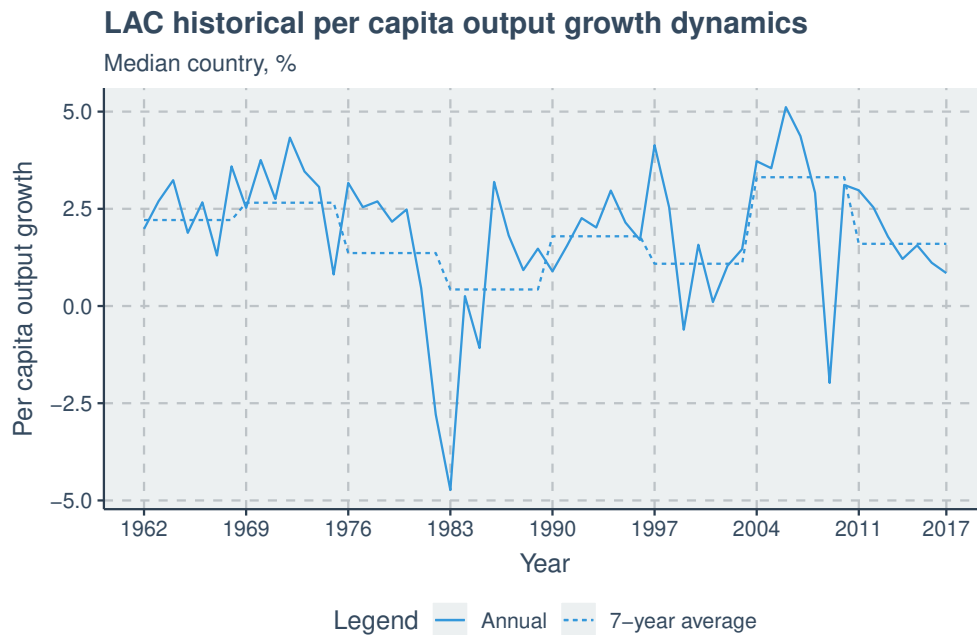


Figure 3.2: Historical median output growth in Latin America and the Caribbean.

after). The experience of relatively higher growth in the earlier periods is especially true in the case of Brazil (as well as Dominican Republic), which explains why, in an aggregate sense, because of the dominant relative size of Brazil within LAC, growth around 1970 is sometimes regarded as the onset of the golden years of LAC growth. Venezuela is a singular case, experiencing its worst growth collapse in the recent period.

To go deeper in the analysis and gauge the role of productivity growth, we first perform a traditional growth accounting exercise in which we decompose per capita output growth into per capita factor accumulation and productivity growth. To focus the analysis on productivity growth, we lump together the contribution of the accumulation of all factors of production to (per capita) output growth. This

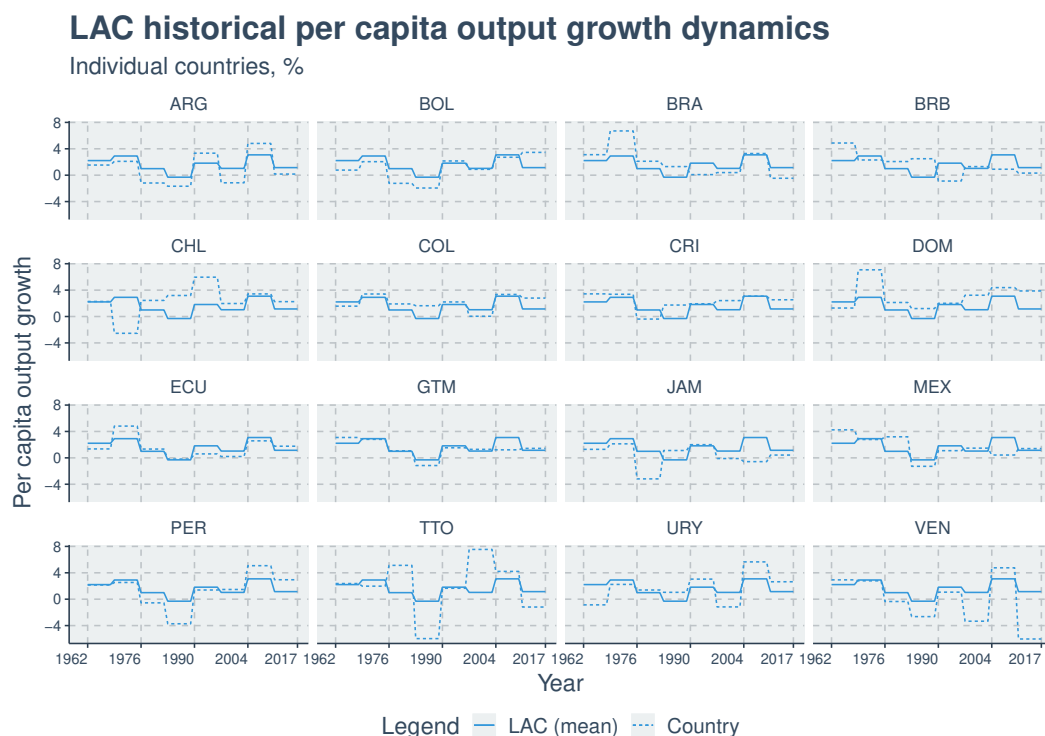


Figure 3.3: Historical output growth in individual countries of Latin America and the Caribbean, each plotted against the LAC mean.

includes the accumulation of physical capital per capita through net investment as well as growth in human capital per capita, including both increases in labor force participation and improvements in the average productive skills of the labor force.⁴ We perform an additive decomposition of the per capita output growth rate in each country into these two broad sources of growth, namely, productivity improvement and factor accumulation. Country growth rates are averaged over the seven years of each period to obtain decompositions for each period, and they are averaged over the

⁴As measured by the wage impact of the additional education received.

16 LAC countries to produce decompositions for LAC as a whole. (See the Statistical Appendix for the sources and methods utilized.)

Decomposing per capita GDP growth into the contributions of factor accumulation and total factor productivity growth, it becomes clear that, in an accounting sense, per capita output growth in LAC has been sustained by factor accumulation. Table 3.1 exhibits this decomposition by period and shows that, in fact, productivity growth has often detracted from output growth. Productivity growth has made a null (actually slightly negative) contribution to cumulative or long-term output growth in LAC both before and after 1990. Factor accumulation, in contrast, has consistently made a positive contribution, virtually the same before and after 1990, and is the reason why LAC's per capita output grew at all. This predominance of factor accumulation holds true in each one of the 16 countries (Figure 3.4 and Figure 3.5). Even in the countries in which productivity growth made a long-term contribution, the contribution of factor accumulation usually dwarfs it.

It is important to recognize what drives TFP growth. In part, TFP growth reflects the economy-wide adoption of technology-related advances that are not embodied in capital investments.⁵ In this regard, low TFP growth points to slow technology absorption or the poor adoption of disembodied new knowledge by firms. However, technology use at the firm level is not the only determinant of TFP. In particular, the level of TFP also reflects the overall efficiency with which factors

⁵To the extent that physical capital service estimations successfully adjust for the quality of the capital stock, productivity estimations reflect only disembodied technological progress. Likewise, human capital measures incorporate quality improvements in the labor force headcount yielded by additional education.

Table 3.1: LAC per capita output growth decomposition.

Period end	Productivity	Factors	Total
1968	1.05	1.16	2.21
1975	0.24	2.67	2.91
1982	-1.72	2.71	0.99
1989	-1.07	0.76	-0.31
1996	0.54	1.29	1.82
2003	-0.77	1.80	1.03
2010	0.77	2.31	3.08
2017	-0.87	2.01	1.15
Averages			
Average pre 1990	-0.37	1.83	1.45
Average post 1990	-0.08	1.85	1.77
Overall average	-0.23	1.84	1.61

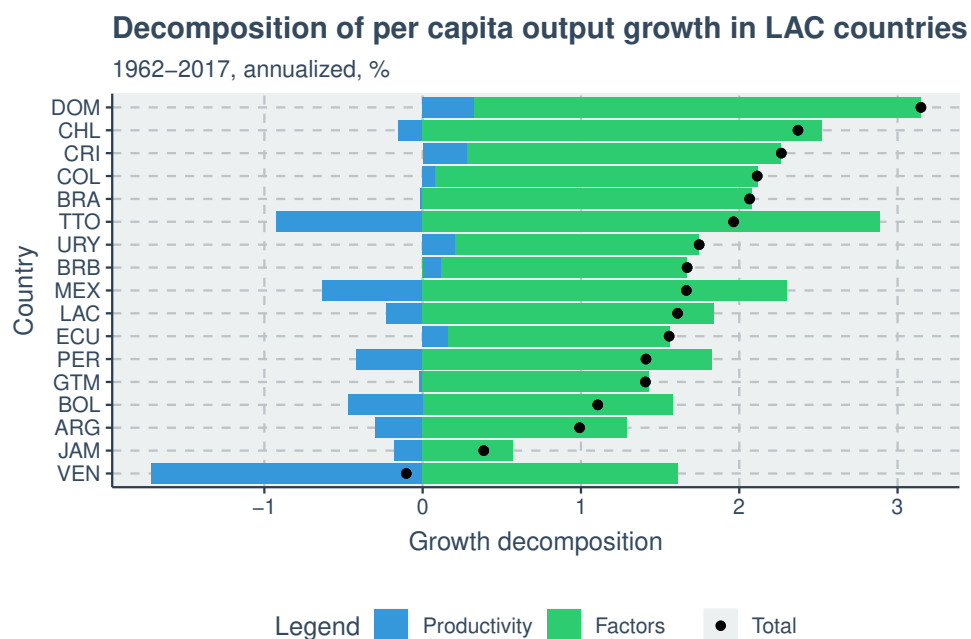


Figure 3.4

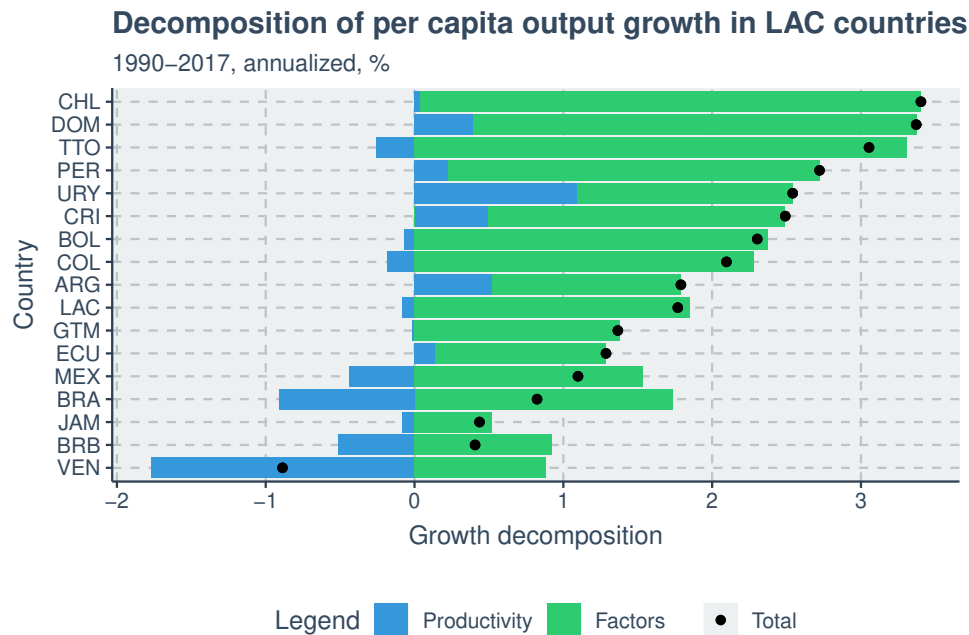


Figure 3.5

of production are allocated throughout the economy.⁶ The suboptimal deployment of public investments and economic distortions in market conditions that are not successfully addressed by public policy (or actually caused by it) lead to investment misallocation across the economy and would be reflected in low TFP. Therefore, worsening misallocation would translate into low TFP growth. Furthermore, factors leading to misallocation may themselves distort technology use decisions and become the reason for slow technological improvement, another source of low TFP growth. It is therefore important to look broadly at public activities and market conditions that influence the aggregate effectiveness with which the factors of production available in the economy are utilized. In particular, the root of productivity deficits may

⁶The effect of the efficiency of the allocation on TFP has been explored in a large literature starting with Restuccia and Rogerson 2008 and Hsieh and Klenow 2009.

be associated with aggregate resource misallocation rather than narrow technology-specific considerations. The previous finding of a small contribution of TFP growth suggests the existence of persistent resource misallocation in LAC countries.

Nonetheless, the dominant role of factor accumulation in long-term growth does not mean that productivity growth was irrelevant in accounting for the experience of LAC. Table 1 suggests that, during the periods when LAC performance is particularly high or low, so is productivity growth. To examine this more closely, we compute the correlation between per capita GDP growth and its two components over the eight periods, revealing that the correlation with productivity growth is 0.78, while the correlation with factor accumulation is only 0.48. (The results are similar if changes in growth rates, that is, accelerations, are considered instead.) The conclusion is that the main driver of the unstable dynamics of LAC output growth is unstable productivity growth, which matches the international evidence uncovered by Easterly and Levine 2001.

The analysis in this section sets the stage for LAC's experience and is informative in the assessment of the region's performance. However, it cannot answer the extent to which this performance is unsatisfactory (is per capita output growth unsuitably low?) and, if so, what are the factors behind the failure. The next section refines this analysis by looking at benchmarks to analyze LAC's performance and answer these questions.

3.3 LAC Performance Gaps

Measuring comparative performance relative to benchmark countries is useful in assessing whether growth is less than what is needed or what might have been expected and, concerning growth diagnosis, in detecting anomalies that reveal specific domestic failures. Underperformance relative to a norm is a key analytic tool in gauging poor performance and discovering the drivers. This section makes intensive use of this approach in a number of ways.

3.3.1 The Evidence from Comparative Development Analysis

Before refining the growth accounting methods utilized in the previous section through the application of a comparative approach, it is useful to review the insights gained from the literature of comparative development analyses on this very subject of the role of productivity in LAC performance. This literature looks at the stocks of factors of production in place (physical and human capital, capital for short) and the level of TFP with which they are utilized to explain the level of output per capita in LAC countries. To answer the question of whether low output is due to low capital or low productivity, it looks at the corresponding output, capital and productivity gaps relative to benchmarks. Because the stock of capital and the level of productivity with which it is utilized result from the cumulative effect of changes over time (net additions to capital and changes in productivity), the findings in this literature are closely related to those from growth accounting over long periods of time.

This brief review of LAC comparative development analysis draws heavily on Daude and Fernández-Arias 2010 and Fernández-Arias and Rodríguez-Apolinar 2016. The main point to highlight from these papers is that low productivity is the main culprit in LAC's disappointingly low GDP per capita. This conclusion is based on a number of claims and observations, as follows:

1. LAC productivity is only about 50% of that of the United States (taken as the leading country), and, in contrast to theory and evidence elsewhere, the gap is now wider than it was at the onset of the debt crisis. Resource misallocation would have produced low levels of TFP and is a natural candidate to explain this finding.
2. LAC's per capita output gap with the United States is increasingly being explained by the productivity gap (rather than by the gap in the stocks of production factors in place).
3. The diversity of country output per capita around the world is matched by a corresponding diversity of productivity levels. The correlation between the two is 0.95. LAC is no exception: the correlation across LAC countries is 0.80. (These high correlations may be rationalized by pointing to the positive feedback loop between higher productivity and higher factor accumulation: higher aggregate productivity provides incentives for higher factor accumulation, and higher factor accumulation may include new vintage capital and skills that facilitate higher aggregate productivity).

4. Despite the distortions in markets and policies underlying factor accumulation, if the region's productivity gap were closed, its per capita output gap would largely disappear over time because of the correspondingly enhanced incentives to invest.
5. However, concerning the reverse direction of causality from factor accumulation to productivity, investment in physical capital appears to be less effective in LAC than in other regions in fostering higher aggregate productivity. This suggests that it has smaller productivity spillovers.

These are all pieces of evidence supporting the idea that LAC's growth underperformance is not associated with the accumulation effort but with the failure to generate productivity growth.

3.3.2 Comparative Growth Accounting

For comparative growth accounting, Figure 3.6 and Figure 3.7 extend the information in Figure 3.4 and Figure 3.5 by showing the contributions of factor accumulation and productivity to per capita output growth for each one of the 71 countries in our world sample (total growth can be read on the iso-growth lines). In virtually all cases, factor growth exceeds productivity growth (that is, the points are above the 45-degree line). The question in this comparative approach is whether LAC countries are anomalous in this world context in ways that are helpful for the assessment and diagnosis of their growth experience.

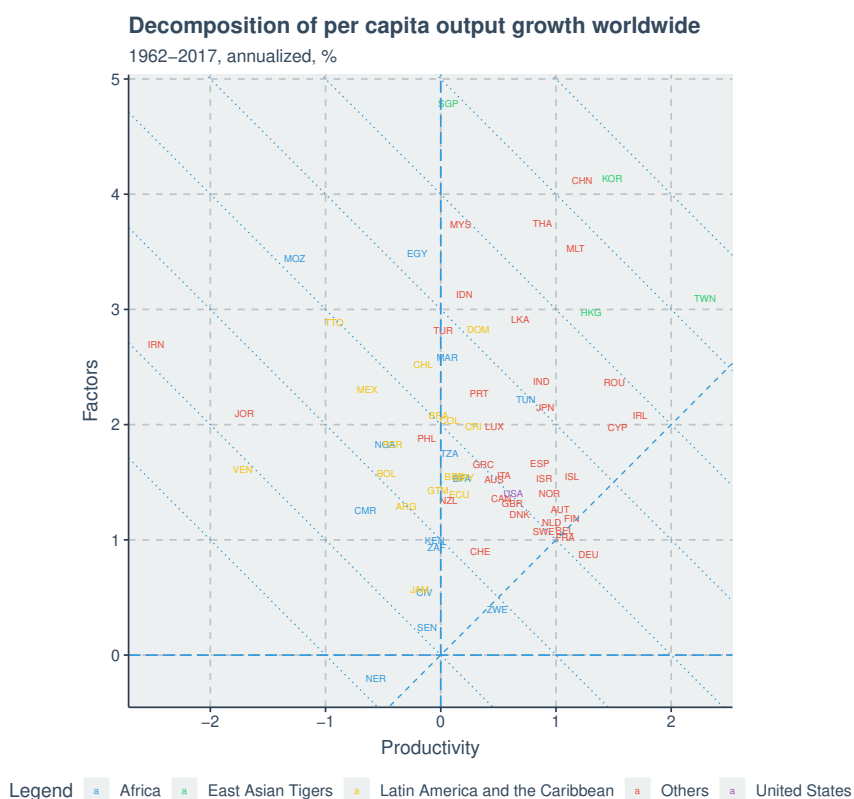


Figure 3.6

Our first step is to consider the growth accounting gaps between LAC and four benchmarks: all 55 non-LAC economies, the 4 East Asian tigers, the 14 African countries, and the United States. (see Statistical Appendix for further details on how this world sample was assembled.) Each one of the benchmarks is useful in probing various dimensions. The rest of the world or non-LAC economies could be considered as the norm, that is, the normal country experience around the world. The specific extra-regional benchmarks represent interesting contrasting scenarios. The East Asian tigers are the paradigmatic development success story of the period. The African countries, on the contrary, conform to a scenario of unsatisfactory development. In



Figure 3.7

each case, we consider the mean country, constructed as the simple average of country growth rates (of those in the LAC region and in each benchmark grouping). Finally, the US benchmark represents the productivity frontier and, more generally, the development frontier towards which successful development ought to converge.

Tables 3.2–3.5 build on Table 3.1 to show the annual growth gaps between LAC and each of the four benchmarks, meaning the LAC growth rates shown in Table 1, minus the corresponding growth rates of the benchmark (so that negative gaps are shortfalls). LAC's poor performance can be characterized by the overall negative gaps in per capita output annual growth over the period. The shortfall is almost a

Table 3.2: LAC per capita output growth gap: non-LAC benchmark

Period end	Productivity	Factors	Total
1968	-0.33	-0.73	-1.05
1975	-0.50	0.04	-0.45
1982	-1.59	0.04	-1.55
1989	-1.35	-0.90	-2.25
1996	0.17	-0.32	-0.15
2003	-1.34	0.19	-1.15
2010	0.45	0.36	0.81
2017	-1.17	0.34	-0.83
Averages			
Average pre 1990	-0.94	-0.39	-1.33
Average post 1990	-0.47	0.14	-0.33
Overall average	-0.71	-0.12	-0.83

full percentage point with respect to the rest of the world or non-LAC economies, meaning that it is substantially below the norm. Had LAC grown over 1962-2017 at the normal rate, its current GDP per capita would be about 50% higher than it actually is. LAC's per capita output growth is only marginally above Africa's and is far below the corresponding rate among the East Asian tigers. LAC also grew more slowly than the most advanced country, the United States, thereby falling further behind the frontier.

However, not all is bad news. The comparison between pre- and post-1990 growth gaps shows clear progress. While per capita output growth in LAC post-1990 is still substantially below the norm (Table 3.2), the shortfall contracted by a full percentage point relative to pre-1990. This enormous progress is insufficient, but it erased most of the initial growth gap. Progress measured against the United States is even greater (Table 3.5). Post-1990, the mean country in LAC actually grew more quickly than

Table 3.3: LAC per capita output growth gap: Africa benchmark

Period end	Productivity	Factors	Total
1968	0.79	0.09	0.88
1975	-0.43	1.08	0.65
1982	-0.31	0.25	-0.07
1989	-0.40	0.53	0.13
1996	1.02	0.52	1.53
2003	-1.48	1.03	-0.46
2010	0.59	-0.22	0.37
2017	-0.47	-0.55	-1.02
Averages			
Average pre 1990	-0.09	0.49	0.40
Average post 1990	-0.09	0.19	0.11
Overall average	-0.09	0.34	0.25

Table 3.4: LAC per capita output growth gap: EAT benchmark

Period end	Productivity	Factors	Total
1968	-1.00	-2.14	-3.14
1975	-1.21	-2.89	-4.10
1982	-2.89	-2.85	-5.75
1989	-3.73	-3.22	-6.95
1996	-0.59	-3.10	-3.68
2003	-0.76	-0.72	-1.48
2010	-0.92	-0.23	-1.15
2017	-1.04	-0.11	-1.15
Averages			
Average pre 1990	-2.21	-2.77	-4.98
Average post 1990	-0.83	-1.04	-1.87
Overall average	-1.52	-1.91	-3.43

Table 3.5: LAC per capita output growth gap: USA benchmark

Period end	Productivity	Factors	Total
1968	-0.26	-1.40	-1.66
1975	0.40	1.11	1.51
1982	-1.55	0.81	-0.74
1989	-2.43	-1.23	-3.66
1996	-0.12	0.37	0.25
2003	-1.84	0.67	-1.17
2010	0.21	2.09	2.30
2017	-1.28	1.06	-0.23
Averages			
Average pre 1990	-0.96	-0.18	-1.14
Average post 1990	-0.76	1.05	0.29
Overall average	-0.86	0.44	-0.42

the United States. This comparative analysis reveals that 1990 was, in fact, pivotal. The growth in LAC was characterized by considerably better growth performance, a fact that was not apparent in the non-comparative analysis in the previous section (Table 3.1). In particular, high per capita output growth in LAC before the debt crisis shown in Table 1 is misleading: those early periods were also periods of high growth throughout the world (in fact, growth gaps during that timeframe are actually negative because the rest of the world actually grew more quickly (Table 3.2), and LAC growth success back then should not be attributed to a special virtue that LAC subsequently lost.

The key question revolves around the role of productivity growth as a contributor to poor performance in this context. The first observation is that productivity growth in LAC is subpar. The four benchmarks consistently show that, overall, LAC has a substantial shortfall in productivity growth. And progress after 1990 has not been

impressive. Indeed, relative to the norm, the shortfall shrank by half, but it was still substantial (Table 3.2). It closed only marginally against the United States (Table 3.5), remaining substantially negative. (There is no progress with respect to Africa, and the progress observed with respect to the East Asian tigers can be attributed to the slowdown among the latter after an exceptional acceleration.) It is also concerning that, in all four benchmarks, the productivity growth shortfall in the period ending in 2017 widened relative to the previous period and was larger than the average shortfall after 1990.

In contrast, the growth contribution of factor accumulation in LAC does not appear to be subpar. Overall, it is virtually at par with the norm among all non-LAC economies, ahead with respect to Africa, and, importantly, about a half percentage point above the United States. (It only lags with respect to the East Asian tigers, substantially as expected.) This encouraging conclusion about the growth contribution of factor accumulation is reinforced by its performance after 1990, which was actually above the norm of non-LAC economies. In fact, factor accumulation strengthened considerably after 1990 with respect to this norm, the East Asian tigers and the United States.

The picture that emerges from this accounting analysis is that per capita output growth in LAC has been sustained by a healthy contribution of factor accumulation that was dragged back by subpar productivity growth. The elimination of the productivity growth shortfall would not only have eliminated this gap, but also incentivized higher factor accumulation, thereby producing further output growth. This picture is empirically consistent with the results of the comparative development

analysis. LAC strengthened both sources of growth after 1990, but productivity growth remained subpar. With a normal rate of productivity growth, LAC would have had normal per capita output growth and would have converged firmly to US output per capita.

3.3.3 Adjusting for Stage of Development

In this section, we test the robustness of the conclusion of failing productivity growth in LAC by refining the comparison using benchmarks to account for expected transitional growth dynamics. It may be argued that the observed subpar performance of LAC countries is a temporary phase in a longer process. If the LAC countries can be anticipated to speed up organically to attain normal growth results in due course, crude comparisons with benchmarks at a point in time might be misleading. In what follows, we look at how the contributions of growth in productivity and factor accumulation tend to evolve over the course of economic development to understand how to adjust growth comparisons with benchmarks by stage of development.

A lower stage of development may be associated with high growth because low levels of capital stock lead to higher investment returns (traditional transitional convergence) and also because there is more low-hanging fruit to facilitate catching up with the productivity frontier (emulating technology as well as sound economic policies and institutions). Yet, country characteristics that lower growth (for instance, dysfunctional policies and institutions) also lead to low levels of development, generating the opposite association between the stage of development and the growth rate of a country. Moreover, underdevelopment itself, whatever the root causes, may

generate political economy conditions inimical to high growth rates. In this exercise, we do not take a position on the causal factors underlying the relationship between backwardness and growth. Our goal is simply a stylized description of how growth normally evolves over the course of economic development, so that a country's normal or expected growth can be accurately ascertained, taking into account the stage of development. Whether or not a lower stage of development is associated, on average, with a growth kick (unconditional transitional convergence) is an empirical matter.

For the purpose at hand, we measure the stage of development of a country as its output per capita relative to the United States at any given time (in logarithmic terms). With this metric of stage of development, transitional convergence would imply that progress in development (per capita output closer to that of the United States) is associated with less growth, yielding a negative coefficient. In contrast, transitional divergence would correspond to a positive coefficient. To the extent that a LAC country is at a different stage of development than the comparator, an adjustment would be needed to leave aside the effect of differences in stages of development and reflect the effective underlying growth shortfall.

Table 3.6 shows three simple regressions to aid in investigating the dynamics of per capita output growth and the contributions of productivity and factor accumulation using the entire world panel. They control for stage of development and time fixed effects for each of the eight periods to isolate worldwide shocks. The point estimates in the third column (per capita output growth) of Table 3.6 are approximately the

sum of the point estimates in the other two columns (sources of growth).⁷ Our sample confirms the standard result of unconditional divergence in per capita output growth, meaning that backwardness is a drag on growth. In our analysis, this pessimistic result derives from a productivity growth rate that is lower among poorer countries, which more than offsets a (statistically insignificant) tendency of transitional convergence associated with the contribution of factor accumulation. (As a robustness test of this characterization of the normal growth evolution over the course of development that could be expected in LAC countries, Table 3.7 eliminates any possible contamination from LAC's own experience by running the same set of regressions restricting the sample to non-LAC economies, obtaining similar results.)

Stage of development could potentially account for part of the growth gaps shown in Tables 3.2–3.5 because LAC and the benchmarks have different outputs per capita. In our sample, LAC countries are, on average, poorer than non-LAC economies, the East Asian tigers and the United States. Relative to these benchmarks, shortfalls in overall growth and in productivity growth may therefore be partly excused (because poorer countries are expected to do worse). However, the estimations of the effects of stage of development on growth comparisons tend to be small and do not change the overall qualitative conclusions of the previous section. Tables 3.8–3.11 show the adjusted growth gaps with respect to each benchmark based on the transitional dynamics estimations of Tables 3.6 and 3.7 and confirm that the qualitative conclusions derived from the raw gaps in Tables 3.2–3.5 remain valid, namely, that failing per capita

⁷Each regression was estimated using OLS (with clustered robust standard errors). While the three separate specifications have correlated errors, a joint SUR regression would not make a difference because they include the same regressors.

Table 3.6: Growth dynamics worldwide

	(1) Productivity growth	(2) Factor accumulation	(3) Per capita output growth
Per capita output gap (rel. USA)	0.26*** (0.079)	-0.054 (0.12)	0.20* (0.12)
year=1968	1.36*** (0.33)	-0.046 (0.26)	1.32*** (0.37)
year=1975	0.65** (0.31)	0.87*** (0.31)	1.53*** (0.37)
year=1982	-0.47 (0.33)	0.92*** (0.31)	0.45 (0.40)
year=1989	0.022 (0.28)	-0.31 (0.29)	-0.29 (0.37)
year=1996	0.44* (0.26)	-0.23 (0.25)	0.21 (0.29)
year=2003	0.30 (0.35)	-0.11 (0.24)	0.19 (0.30)
year=2010	0.42 (0.27)	0.28 (0.21)	0.70** (0.27)
year=2017	0 (.)	0 (.)	0 (.)
Constant	0.34 (0.23)	1.69*** (0.23)	2.03*** (0.27)
Observations	568	568	568

Standard errors in parentheses. Clustering is at country level.

Regression equation: $g_{it} = \alpha + \gamma_t + \beta \left(\log\left(\frac{\text{cgdp}_{oit}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{USA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$

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

Table 3.7: Growth dynamics in non-LAC countries

	(1)	(2)	(3)
	Productivity growth	Factor accumulation	Per capita output growth
Per capita output gap (rel. USA)	0.27*** (0.080)	-0.096 (0.13)	0.17 (0.13)
year=1968	1.20*** (0.36)	0.17 (0.30)	1.37*** (0.42)
year=1975	0.52 (0.36)	0.92** (0.37)	1.44*** (0.42)
year=1982	-0.36 (0.39)	0.97** (0.38)	0.61 (0.46)
year=1989	0.067 (0.31)	-0.042 (0.31)	0.025 (0.42)
year=1996	0.15 (0.24)	-0.095 (0.29)	0.051 (0.32)
year=2003	0.34 (0.37)	-0.086 (0.29)	0.25 (0.33)
year=2010	0.055 (0.24)	0.27 (0.25)	0.32 (0.25)
year=2017	0 (.)	0 (.)	0 (.)
Constant	0.60*** (0.18)	1.57*** (0.25)	2.16*** (0.29)
Observations	440	440	440

Standard errors in parentheses. Clustering is at country level.

Regression equation: $g_{it} = \alpha + \gamma_t + \beta \left(\log\left(\frac{\text{cgdp}_{it}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{USA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$

Notes: Only non-LAC sample.

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

output growth in LAC can be traced to subpar productivity growth. If anything, these adjustments reinforce the conclusion that LAC's productivity growth is failing by showing a substantial underlying shortfall also with respect to Africa.

To visualize growth gaps over time, we consider time series based on seven-year rolling windows. In this way, short-term effects are still filtered by seven-year averages, but subperiods of interest are not assumed exogenously. In this visualization, window averages are shown at the window center (that is, the fourth year). We consider the evolution of adjusted growth gaps in output per capita and the sources relative to non-LAC economies at the regional level and also by country. Results are shown in Figure 3.8 for LAC and Figures 3.9–3.11 for each LAC country. In these figures, the reader may recognize the dating of particular growth performance events in individual countries and trace them to their sources.

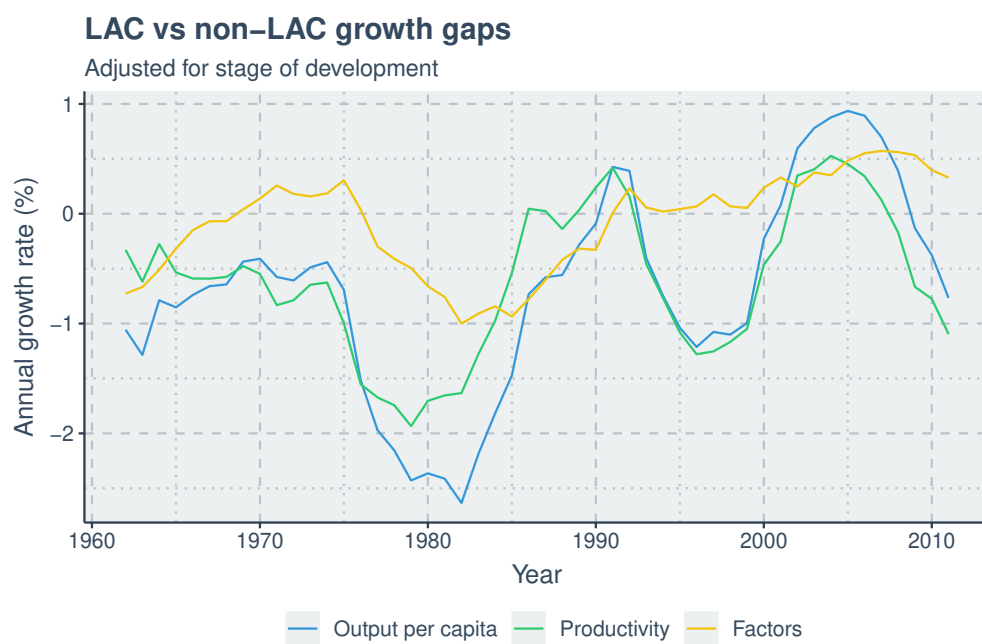


Figure 3.8

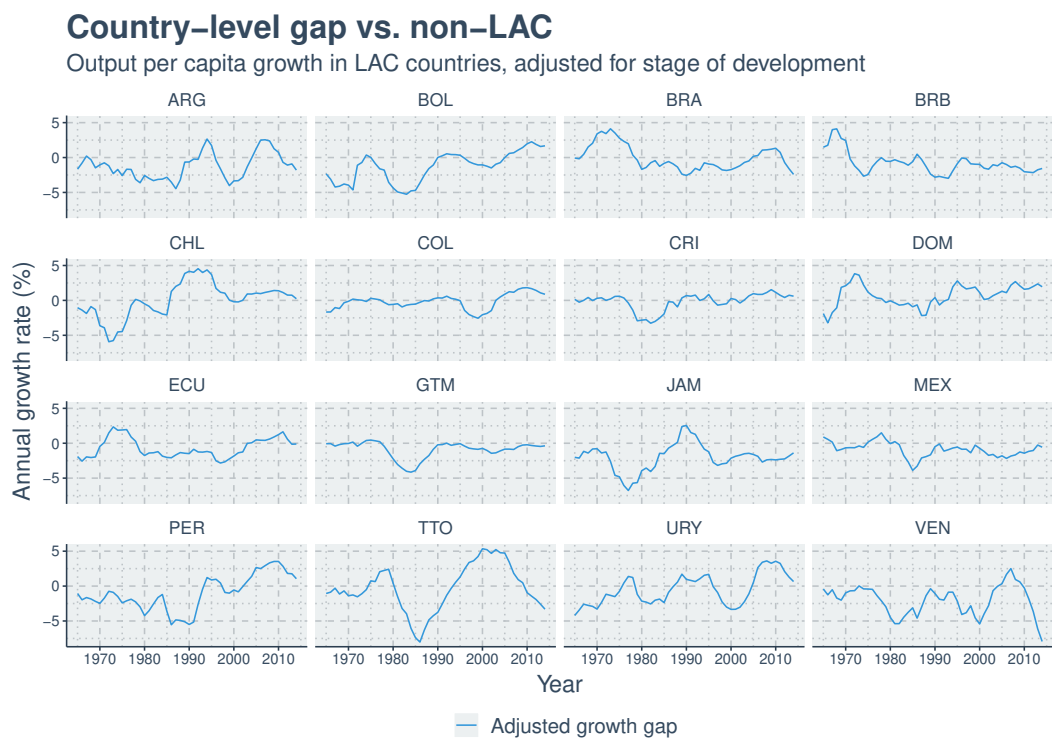


Figure 3.9

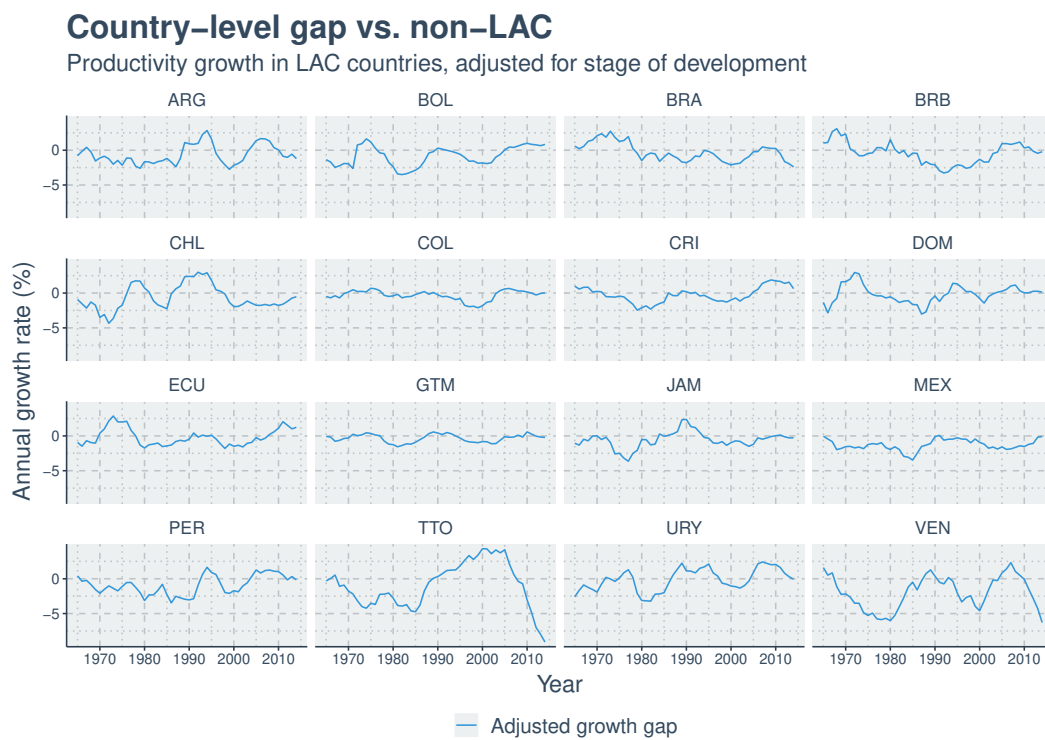


Figure 3.10

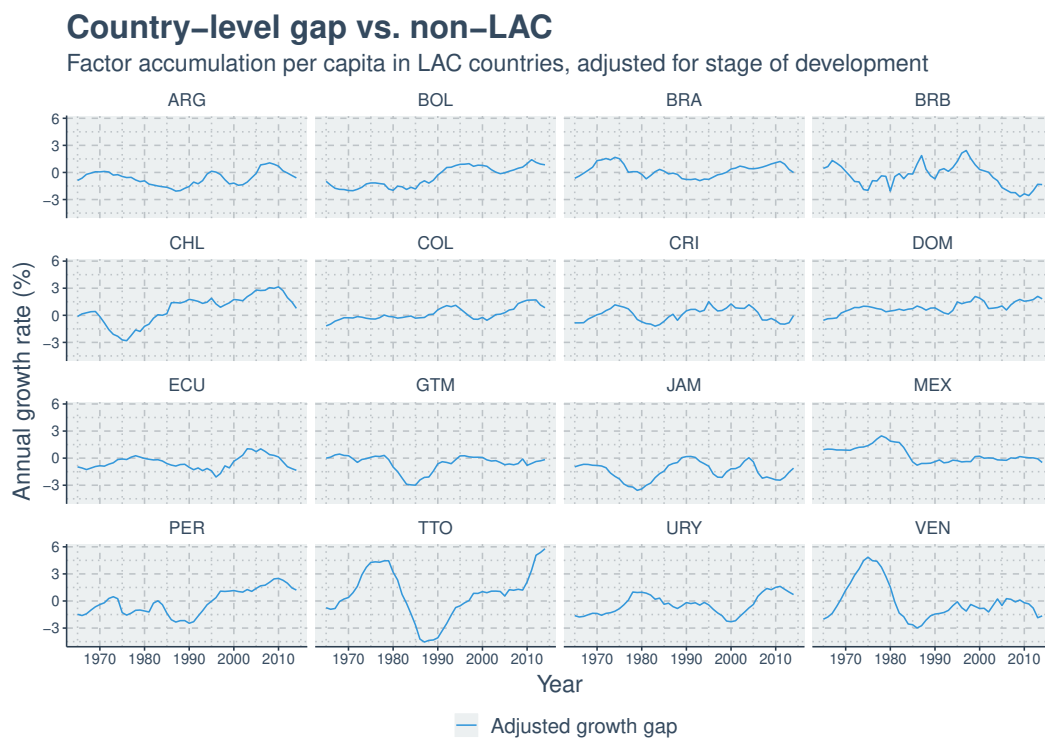


Figure 3.11

Table 3.8: LAC per capita output growth gap: non-LAC benchmark

Period end	Produc -tivity	Prod. (adj.)	Prod. (adj., robust)	Factors	Fact. (adj.)	Fact. (adj., robust)	Total	Total (adj.)	Total (adj., robust)
1968	-0.33	-0.33	-0.33	-0.73	-0.73	-0.73	-1.05	-1.06	-1.06
1975	-0.50	-0.48	-0.47	0.04	0.04	0.04	-0.45	-0.44	-0.44
1982	-1.59	-1.55	-1.55	0.04	0.03	0.03	-1.55	-1.52	-1.52
1989	-1.35	-1.28	-1.27	-0.90	-0.92	-0.93	-2.25	-2.19	-2.20
1996	0.17	0.24	0.25	-0.32	-0.34	-0.35	-0.15	-0.09	-0.10
2003	-1.34	-1.25	-1.24	0.19	0.17	0.15	-1.15	-1.08	-1.09
2010	0.45	0.53	0.54	0.36	0.34	0.33	0.81	0.88	0.86
2017	-1.17	-1.09	-1.09	0.34	0.32	0.31	-0.83	-0.77	-0.78
Averages									
Average pre 1990	-0.94	-0.91	-0.91	-0.39	-0.39	-0.40	-1.33	-1.30	-1.30
Average post 1990	-0.47	-0.39	-0.39	0.14	0.12	0.11	-0.33	-0.27	-0.28
Overall average	-0.71	-0.65	-0.65	-0.12	-0.13	-0.14	-0.83	-0.78	-0.79

Table 3.9: LAC per capita output growth gap: EAT benchmark

Period end	Produc- tivity	Prod. (adj.)	Prod. (adj., robust)	Factors	Fact. (adj.)	Fact. (adj., robust)	Total	Total (adj.)	Total (adj., robust)
1968	-1.00	-1.09	-1.09	-2.14	-2.12	-2.11	-3.14	-3.21	-3.20
1975	-1.21	-1.19	-1.19	-2.89	-2.89	-2.89	-4.10	-4.08	-4.08
1982	-2.89	-2.78	-2.77	-2.85	-2.88	-2.90	-5.75	-5.66	-5.67
1989	-3.73	-3.51	-3.50	-3.22	-3.26	-3.30	-6.95	-6.77	-6.80
1996	-0.59	-0.29	-0.28	-3.10	-3.16	-3.21	-3.68	-3.45	-3.49
2003	-0.76	-0.41	-0.40	-0.72	-0.79	-0.85	-1.48	-1.21	-1.25
2010	-0.92	-0.57	-0.56	-0.23	-0.30	-0.36	-1.15	-0.88	-0.92
2017	-1.04	-0.71	-0.70	-0.11	-0.18	-0.23	-1.15	-0.89	-0.94
Averages									
Average pre 1990	-2.21	-2.14	-2.14	-2.77	-2.79	-2.80	-4.98	-4.93	-4.94
Average post 1990	-0.83	-0.50	-0.49	-1.04	-1.11	-1.16	-1.87	-1.61	-1.65
Overall average	-1.52	-1.32	-1.31	-1.91	-1.95	-1.98	-3.43	-3.27	-3.29

Table 3.10: LAC per capita output growth gap: AFR benchmark

Period end	Produc -tivity	Prod. (adj.)	Prod. (adj., robust)	Factors	Fact. (adj.)	Fact. (adj., robust)	Total	Total (adj.)	Total (adj., robust)
1968	0.79	0.53	0.52	0.09	0.14	0.19	0.88	0.68	0.71
1975	-0.43	-0.70	-0.71	1.08	1.14	1.18	0.65	0.44	0.47
1982	-0.31	-0.58	-0.59	0.25	0.30	0.35	-0.07	-0.28	-0.25
1989	-0.40	-0.67	-0.68	0.53	0.59	0.63	0.13	-0.08	-0.05
1996	1.02	0.70	0.69	0.52	0.58	0.63	1.53	1.28	1.32
2003	-1.48	-1.81	-1.83	1.03	1.10	1.15	-0.46	-0.72	-0.67
2010	0.59	0.24	0.23	-0.22	-0.15	-0.09	0.37	0.10	0.14
2017	-0.47	-0.81	-0.82	-0.55	-0.48	-0.42	-1.02	-1.29	-1.25
Averages									
Average pre 1990	-0.09	-0.35	-0.36	0.49	0.54	0.59	0.40	0.19	0.22
Average post 1990	-0.09	-0.42	-0.43	0.19	0.26	0.32	0.11	-0.16	-0.11
Overall average	-0.09	-0.39	-0.40	0.34	0.40	0.45	0.25	0.02	0.05

Table 3.11: LAC per capita output growth gap: USA benchmark

Period end	Produc- tivity	Prod. (adj.)	Prod. (adj., robust)	Factors	Fact. (adj.)	Fact. (adj., robust)	Total	Total (adj.)	Total (adj., robust)
1968	-0.26	0.13	0.15	-1.40	-1.48	-1.55	-1.66	-1.35	-1.40
1975	0.40	0.78	0.80	1.11	1.03	0.97	1.51	1.82	1.77
1982	-1.55	-1.16	-1.14	0.81	0.73	0.66	-0.74	-0.43	-0.48
1989	-2.43	-1.99	-1.97	-1.23	-1.32	-1.39	-3.66	-3.31	-3.37
1996	-0.12	0.32	0.33	0.37	0.28	0.20	0.25	0.59	0.53
2003	-1.84	-1.40	-1.38	0.67	0.58	0.51	-1.17	-0.82	-0.88
2010	0.21	0.61	0.63	2.09	2.01	1.94	2.30	2.62	2.57
2017	-1.28	-0.92	-0.91	1.06	0.98	0.92	-0.23	0.06	0.01
Averages									
Average pre 1990	-0.96	-0.56	-0.54	-0.18	-0.26	-0.33	-1.14	-0.82	-0.87
Average post 1990	-0.76	-0.35	-0.33	1.05	0.96	0.89	0.29	0.61	0.56
Overall average	-0.86	-0.45	-0.44	0.44	0.35	0.28	-0.42	-0.10	-0.16

3.4 LAC Performance in Panel Regressions

We use a panel regression framework to show in a more compact way how the performance of LAC countries deviates from the world experience and attach statistical significance to these deviations. Table 3.12 extends the basic set of three growth regressions of Table 3.6 by adding a LAC dummy modeling a regional fixed effect to contrast the LAC experience with the rest of the world. These growth regressions continue to control for stage of development as well as worldwide growth changes reflected in time period fixed effects, with the time series constructed using seven-year rolling windows within 1962-2017.

This simple set of regressions shows stark results that reaffirm the conclusion that LAC's per capita output growth is below expectation and that the shortfall is essentially caused by abnormally low productivity growth, rather than factor accumulation weakness. In fact, the negative LAC fixed effect for productivity growth is large (and statistically significant with high confidence), but this is not

Table 3.12: Statistical significance of LAC growth gap (Non-LAC Benchmark)

	(1) Productivity growth	(2) Factor accumulation	(3) Per capita output growth
Per capita output gap (rel. USA)	0.22*** (0.076)	-0.033 (0.13)	0.18 (0.13)
LAC	-0.62*** (0.17)	-0.086 (0.22)	-0.70** (0.28)
Observations	3550	3550	3550

Standard errors in parentheses. Clustering is at country level.

Regression equation: $g_{it} = \alpha + \sigma \mathbf{1}_{\text{LAC}} + \gamma_t + \beta \left(\log\left(\frac{\text{cgdp}_{it}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{USA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$

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

the case of the one for the contribution of factor accumulation, which translates into a considerable (and also statistically highly significant) overall per capita output growth shortfall of 0.70 percentage points per year relative to normal. LAC per capita output growth in 1962-2017 is substantially below expectation. The shortfall of productivity growth is the predominant component, amounting to about 90% of this overall growth shortfall. Because the regression controls for the per capita output gap (the estimated effect of which is about the same as in Table 3.6), these shortfalls are implicitly adjusted by stage of development.

Table 3.13 introduces two LAC dummies, pre- and post-1990, and confirms that, in the latter period, there was substantial improvement in both productivity and factor growth gaps of about half of a percentage point. Nonetheless, there is still a substantial shortfall in productivity growth of about 0.3 percentage points per year that more than offsets a factor accumulation contribution slightly above the norm. The conclusion is that, in the current post-1990 regime, the contribution of factor accumulation is in line with non-LAC indicators, but productivity growth, while improved relative to pre-1990, is still subpar.⁸

How do individual LAC countries deviate from this poor average performance? Table 3.14 opens up the LAC dummy in Table 3.12 into a dummy for each LAC country. The conclusion is that the average analysis holds well in each of the 16 countries in our sample. It is remarkable that there is a productivity growth shortfall in every single LAC country in our sample, almost always highly significant, that leads to an overall shortfall in per capita output growth except in Chile and Dominican

⁸Pre- and post-1990 dummies are statistically different at the 8.4% level. The post-1990 dummy is significantly different from zero at the 10.2% level.

Table 3.13: Statistical significance of LAC growth gap, pre- and post-1990 (Non-LAC Benchmark)

	(1) Productivity growth	(2) Factor accumulation	(3) Per capita output growth
Per capita output gap (rel. USA)	0.22*** (0.076)	-0.030 (0.13)	0.19 (0.13)
LAC $\times$ pre 1990	-0.93*** (0.28)	-0.33 (0.28)	-1.26*** (0.38)
LAC $\times$ post 1990	-0.31 (0.19)	0.16 (0.26)	-0.15 (0.34)
Observations	3550	3550	3550

Standard errors in parentheses. Clustering is at country level.

Regression equation:

$$g_{it} = \alpha + \sigma_1 \mathbf{1}_{\text{LAC,pre1990}} + \sigma_2 \mathbf{1}_{\text{LAC,post1990}} + \gamma_t + \beta \left(\log\left(\frac{\text{cgdp}_{oit}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{USA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$$

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

Republic (while the experience with factor accumulation is mixed, above the norm in a number of countries). Figure 3.12 visualizes the results showing productivity and factor accumulation (adjusted) growth gaps for each LAC country relative to the non-LAC group as measured by the fixed effects over 1962-2017.

The progress in the mean country of LAC after 1990 is supported by improvements in a number of countries. Table 3.15 opens up the pre- and post-1990 LAC dummies in Table 3.13 into country dummies to uncover country diversity in the evolution of (adjusted) growth gaps. In particular, Figure 3.13 shows the productivity growth shortfalls pre- and post-1990 for each one of the 16 LAC countries. After 1990, comparative productivity growth improved in most countries (they are above the 45-degree line), with the exception of Barbados, Brazil and Colombia). Nonetheless, in the current post-1990 regime, based on these estimations, productivity growth in the LAC countries in our sample is still largely subpar, with the exception of Argentina,

Table 3.14: Statistical significance of LAC individual country growth gaps (Non-LAC Benchmark)

	(1) Productivity	(2) Factors	(3) Output per capita
Per capita output gap (relative to USA)	0.23***	-0.055	0.17
Argentina	-0.63***	-0.62***	-1.25***
Bolivia	-0.84***	-0.50*	-1.34***
Brazil	-0.28**	0.22	-0.059
Barbados	-0.43***	-0.35**	-0.79***
Chile	-0.63***	0.69***	0.061
Colombia	-0.31***	0.15	-0.17
Costa Rica	-0.25**	0.078	-0.17
Dominican Republic	-0.15	0.87***	0.72***
Ecuador	-0.18	-0.49***	-0.67***
Guatemala	-0.33**	-0.57***	-0.91***
Jamaica	-0.58***	-1.46***	-2.04***
Mexico	-1.30***	0.41***	-0.89***
Peru	-0.90***	-0.12	-1.01***
Trinidad & Tobago	-0.96***	0.71***	-0.25
Uruguay	-0.10	-0.39**	-0.49**
Venezuela	-1.97***	-0.083	-2.05***
Observations	3550	3550	3550

Standard errors omitted for clarity. Clustering is at country level.

Regression equation: $g_{it} = \alpha + \omega_i + \gamma_t + \beta \left(\log\left(\frac{\text{cgdp}_{it}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{USA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$

Estimated values of ω_i for each country i shown above.

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

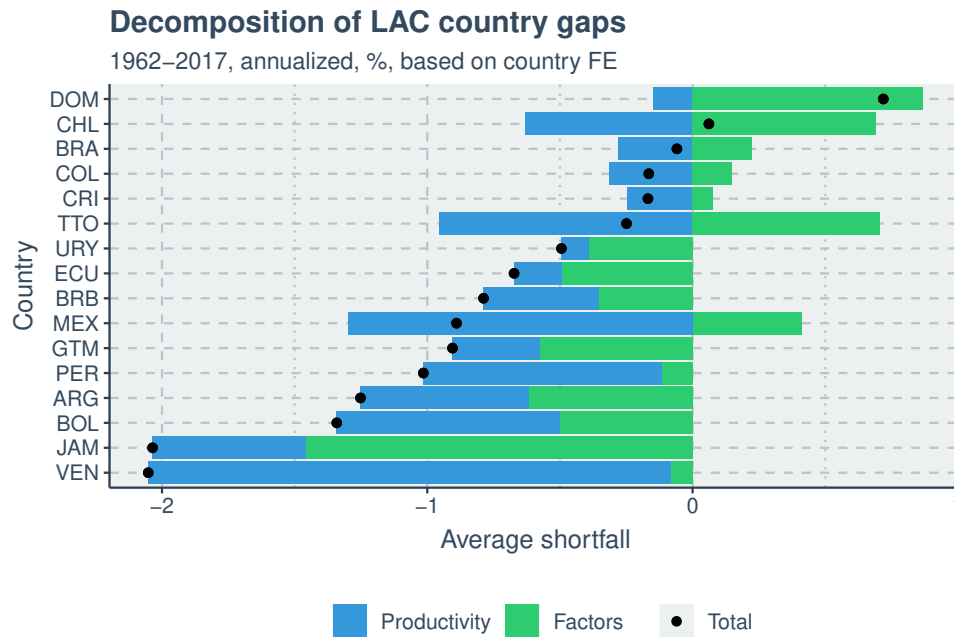


Figure 3.12

Costa Rica, Dominican Republic, Trinidad and Tobago, and Uruguay.⁹ Furthermore, at par productivity growth (at the rate of a comparable non LAC country) is not sufficient to converge to the rate of productivity growth of the United States. In fact, even after 1990, productivity growth in every LAC country is below that in the United States with the only exception of Uruguay. If the stricter success standard of converging to the productivity frontier is applied, virtually no LAC country has had successful productivity growth since 1990.

⁹Productivity growth in Trinidad and Tobago has plummeted to historically low levels in recent years.

Table 3.15: Statistical significance of LAC individual country growth gaps, pre- and post-1990 (Non-LAC Benchmark)

	(1) Productivity growth	(2) Factor accumulation	(3) Per capita output growth
Per capita output gap (relative to USA)	0.23***	-0.057	0.18
ARG pre-1990	-1.28***	-0.87***	-2.14***
ARG post-1990	0.011	-0.37**	-0.36*
BOL pre-1990	-1.39***	-1.55***	-2.94***
BOL post-1990	-0.27	0.54**	0.27
BRA pre-1990	0.39**	0.30	0.70**
BRA post-1990	-0.95***	0.14	-0.81***
BRB pre-1990	0.16	-0.21	-0.059
BRB post-1990	-1.03***	-0.49***	-1.52***
CHL pre-1990	-0.94***	-0.55***	-1.49***
CHL post-1990	-0.32***	1.93***	1.61***
COL pre-1990	-0.10	-0.31	-0.41
COL post-1990	-0.52***	0.60***	0.079
CRI pre-1990	-0.61***	-0.17	-0.77***
CRI post-1990	0.12	0.32*	0.44**
DOM pre-1990	-0.42**	0.51**	0.087
DOM post-1990	0.13	1.23***	1.36***
ECU pre-1990	-0.19	-0.51**	-0.70**
ECU post-1990	-0.17	-0.48**	-0.65***
GTM pre-1990	-0.39*	-0.83***	-1.22***
GTM post-1990	-0.26*	-0.33	-0.59**
JAM pre-1990	-0.86***	-1.68***	-2.54***
JAM post-1990	-0.28*	-1.24***	-1.53***
MEX pre-1990	-1.64***	0.97***	-0.67**
MEX post-1990	-0.96***	-0.15	-1.11***
PER pre-1990	-1.58***	-1.01***	-2.60***
PER post-1990	-0.21	0.78***	0.58**
TTO pre-1990	-2.43***	0.56***	-1.87***
TTO post-1990	0.50***	0.86***	1.36***
URY pre-1990	-0.92***	-0.54***	-1.46***
URY post-1990	0.71***	-0.24	0.47**
VEN pre-1990	-2.58***	0.50**	-2.07***
VEN post-1990	-1.36***	-0.67***	-2.03***
Observations	3550	3550	3550

Standard errors omitted for clarity. Clustering is at country level.

Regression equation: $g_{it} = \alpha + \omega_{i\tau} + \gamma_t + \beta \left(\log\left(\frac{cgdp_{it}}{pop_{it}}\right) - \log\left(\frac{cgdp_{USA,t}}{pop_{USA,t}}\right) \right) + \epsilon_{it}$

Variable τ is equal to 1 if $t > 1990$, 0 otherwise. Estimated values of $\omega_{i\tau}$ for each country i shown above.

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

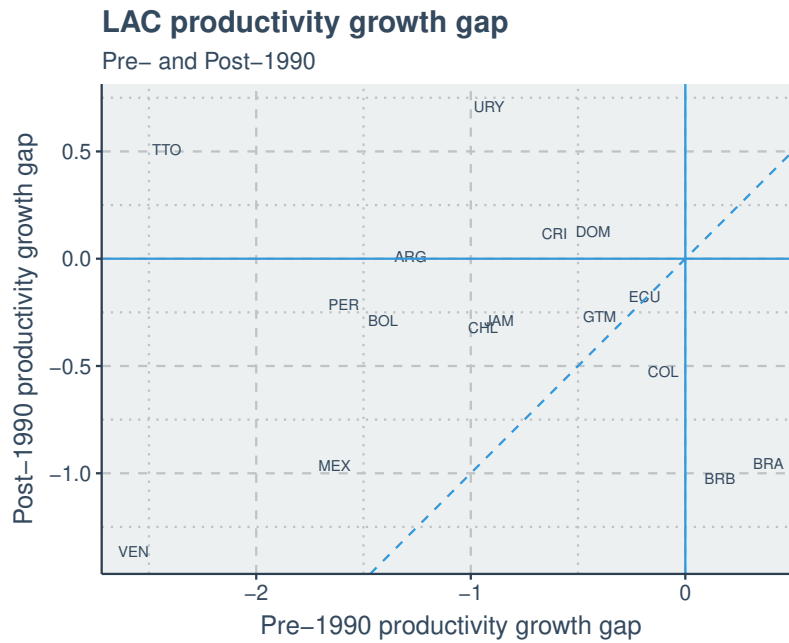


Figure 3.13

3.5 Productivity Growth and Inequality

This section explores connections between low productivity growth and high inequality, both salient characteristics of the region. The objective is to find clues that may help explain the growth gaps uncovered in the previous section.

There is a tentative consensus that inequality limits the opportunities of the disfavored, undermining human capital accumulation, and may cause lower and distorted investment because of political and economic instability (Ostry et al. 2014). In the extreme, it may lead to a fractious political economy that threatens the workings of market economies. Inequality is also often associated with large informal sectors, which may lead to an economic fabric overwhelmed by stagnant traditional firms. It stands to reason to think that these factors may slow productivity growth.

By contrast, there is the opposite view that inequality fosters growth because, for example, it facilitates the accumulation of a critical mass of investable resources.

The findings of empirical analyses on the relation of inequality and growth are not consistent or robust. One reason may be that such a relationship is contaminated by distortionary inequality policies, which may vary widely across space and time. Furthermore, it is clear that growth may also have an important effect on inequality, through, for instance, the compositional effects of the transition from traditional to modern economies, such as Kuznets' transition from agriculture to manufacturing and other current processes of structural transformation. Similarly, underlying economic conditions may impact growth and inequality, such as distortions that favor the emergence of informal enterprises and segmented markets. The reverse causation and spurious correlation channels may statistically confound the causal impact of inequality on growth.

In the empirical analysis in this section, we do not attempt to address these issues of omitted variables and reverse causation and therefore do not claim any policy implication. We extend the basic regressions of the previous section to explore whether inequality accompanies poor growth experiences, with a focus on whether inequality is associated with the subpar productivity growth in LAC. Consistent with our previous approach of controlling for stage of development, we also condition the association between inequality and growth to the stage of development.¹⁰

¹⁰As shown by Barro 2000, this conditioning may be important. In his growth model, Barro finds that inequality retards growth in poor countries and encourages growth in richer countries (with little overall relationship). The vast majority of countries in our sample are in the richer set, and we disregard this interaction.

Inequality data on our sample is from the SWIID database.¹¹ This includes consistently estimated series of the Gini index on disposable income for the most extensive sample we found. Using this dataset, we lost six countries from the growth panel, and, on many other countries, inequality information is missing for the first several years, before 1980. For this reason, the 3550 data points in our balanced panel are reduced to 2234.

Given this limitation, we first checked that the key findings in the previous section still hold in the smaller panel, namely, the underperformance of LAC productivity growth, and then analyzed the issue of inequality within that sample.¹² The main findings in the previous section concerning LAC fixed effects holds in the smaller sample (shown in Tables 3.16–3.17). In particular, we find an equally significant shortfall of 0.66 for productivity growth (instead of 0.62) over the entire period. When pre-1990 and post-1990 LAC dummies are used, this smaller sample yields a somewhat larger shortfall pre-1990 and a similar post-1990 shortfall. Productivity growth is still marginally divergent (but insignificantly so). All in all, the findings associated with this smaller dataset are qualitatively similar to the ones found previously and support using it to analyze the difference that inequality makes and whether it may be a plausible proximate explanation of the underperformance of LAC productivity growth estimated in the previous section.

¹¹See Solt 2020; SWIID (Standardized World Income Inequality Database), Frederick Solt, Department of Political Science, University of Iowa, Iowa City, IA, <http://fsolt.org/swiid/>.

¹²We also experimented with a variety of extrapolating equations to estimate missing inequality information using output per capita series as driving variables and, to augment the restricted sample, allowed country and time dummies, but did not find any reliable specification to model the change in country Gini indexes over time.

Table 3.16: Statistical significance of LAC growth gap (Non-LAC Benchmark, country-years with gini data)

	(1) Productivity growth	(2) Factor accumulation	(3) Per capita output growth
Per capita output gap (rel. USA)	0.030 (0.11)	-0.19 (0.16)	-0.16 (0.16)
LAC	-0.66*** (0.19)	-0.062 (0.25)	-0.72** (0.30)
Observations	2234	2234	2234

Standard errors in parentheses. Clustering is at country level.

Regression equation: $g_{it} = \alpha + \sigma \mathbf{1}_{\text{LAC}} + \gamma_t + \beta \left(\log\left(\frac{\text{cgdp}_{it}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{USA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$

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

Table 3.17: Statistical significance of LAC growth gap, pre- and post-1990 (Non-LAC Benchmark, country-years with gini data)

	(1) Productivity growth	(2) Factor accumulation	(3) Per capita output growth
Per capita output gap (rel. USA)	0.029 (0.11)	-0.20 (0.16)	-0.17 (0.16)
LAC $\times$ pre 1990	-1.38*** (0.33)	-0.47 (0.35)	-1.84*** (0.47)
LAC $\times$ post 1990	-0.27 (0.23)	0.16 (0.30)	-0.10 (0.36)
Observations	2234	2234	2234

Standard errors in parentheses. Clustering is at country level.

Regression equation:

$g_{it} = \alpha + \sigma_1 \mathbf{1}_{\text{LAC,pre1990}} + \sigma_2 \mathbf{1}_{\text{LAC,post1990}} + \gamma_t + \beta \left(\log\left(\frac{\text{cgdp}_{it}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{USA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$

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

Taking Tables 3.16–3.17 as our baseline for this section, our next step is to extend the data, including the income inequality Gini index (Tables 3.18–3.19). More inequality corresponds to a higher Gini index, so that a negative coefficient estimate means that high inequality is associated with low growth.¹³ In both tables, this measure of income inequality appears to be an adverse factor for productivity growth with very high statistical significance. But it is largely irrelevant for the overall growth of output per capita because of its offsetting positive association with factor accumulation. Since the regression also includes the per capita output gap as a control, the inequality effect is conditional on the stage of development. Having established that inequality is a productivity covariate worth exploring, the question becomes the following: can income inequality account for the LAC productivity growth shortfall? More generally, is subpar LAC overall growth performance associated with a highly unequal status (given the stage of development in LAC)? To answer this question we examine how LAC fixed effect estimates change when we control for income inequality..

Concerning productivity growth, Table 3.18 shows that, compared with Table 3.16, the LAC productivity growth shortfall over the entire period is substantially reduced to a statistically insignificant estimation of 0.12 points (from 0.66 points). In other words, high inequality in LAC may largely account for the productivity growth shortfall. In fact, in the post-1990 subperiod, it appears that it overexplains the productivity growth gap (Table 3.19).

¹³We also experimented with a quadratic term and did not obtain any evidence of a non-monotonic effect in our sample.

Table 3.18: Statistical significance of LAC growth gap (Non-LAC Benchmark)

	(1)	(2)	(3)
	Productivity growth	Factor accumulation	Per capita output growth
Gini coefficient	-0.058*** (0.014)	0.050 (0.035)	-0.0073 (0.033)
Per capita output gap (rel. USA)	-0.27** (0.14)	0.071 (0.25)	-0.20 (0.23)
LAC	-0.12 (0.21)	-0.54 (0.45)	-0.66 (0.48)
Observations	2234	2234	2234

Standard errors in parentheses. Clustering is at country level.

Regression equation:

$$g_{it} = \alpha + \sigma \mathbf{1}_{\text{LAC}} + \gamma_t + \beta_1 \text{Gini}_{it} + \beta_2 \left(\log\left(\frac{\text{cgdp}_{oit}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{oUSA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$$

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

Table 3.19: Statistical significance of LAC growth gap, pre- and post-1990 (Non-LAC Benchmark)

	(1)	(2)	(3)
	Productivity growth	Factor accumulation	Per capita output growth
Gini coefficient	-0.055*** (0.013)	0.053 (0.036)	-0.0020 (0.033)
Per capita output gap (rel. USA)	-0.26* (0.13)	0.082 (0.25)	-0.18 (0.22)
LAC $\times$ pre 1990	-0.78** (0.37)	-1.04* (0.57)	-1.82*** (0.63)
LAC $\times$ post 1990	0.21 (0.24)	-0.29 (0.44)	-0.087 (0.50)
Observations	2234	2234	2234

Standard errors in parentheses. Clustering is at country level.

Regression equation:

$$g_{it} = \alpha + \sigma_1 \mathbf{1}_{\text{LAC,pre1990}} + \sigma_2 \mathbf{1}_{\text{LAC,post1990}} + \gamma_t + \beta_1 \text{Gini}_{it} + \beta_2 \left(\log\left(\frac{\text{cgdp}_{oit}}{\text{pop}_{it}}\right) - \log\left(\frac{\text{cgdp}_{oUSA,t}}{\text{pop}_{USA,t}}\right) \right) + \epsilon_{it}$$

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

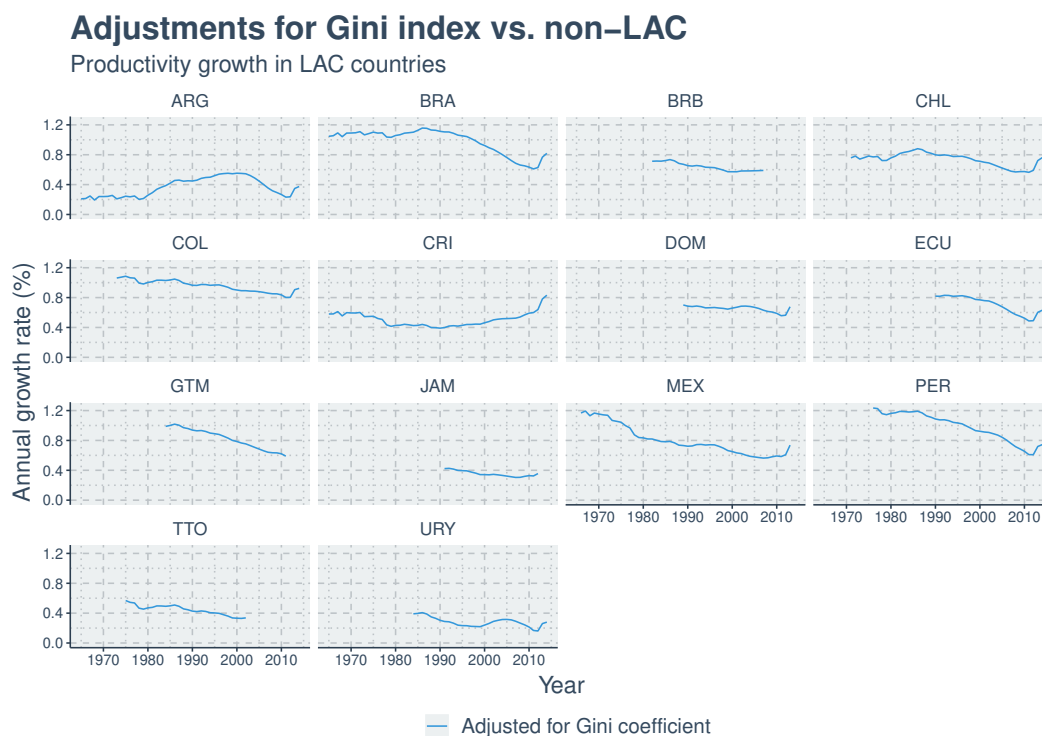


Figure 3.14

Figure 3.14 shows the productivity growth gap accounted for by inequality in each country over time, so that a positive number reflects the portion of the gap accounted for by inequality. Because each Latin American country is more unequal than the average extraregional country, the Gini index consistently accounts for a portion of the productivity growth gap (or may overexplain it).¹⁴ Nonetheless, in most countries, this inequality effect shows a tendency to decline over time as the inequality gap in LAC countries tend to diminish.

However, inequality does not account for the shortfall of overall per-capita output growth because high inequality is also associated with faster factor accumulation

¹⁴Bolivia and Venezuela were dropped because of a lack of inequality data.

(compare Table 3.18 with Table 3.16)). When we control for inequality, LAC exhibits a large shortfall in factor accumulation, 0.54 points, so the unexplained overall gap in per capita output growth largely remains. The comparison between Table 3.19 and 17 yields the same qualitative results in both the pre- and post-1990 subperiods. With regards to the post-1990 subperiod, once we control for inequality, LAC actually shows above-par productivity growth, which is offset by subpar factor accumulation (both gaps are statistically insignificant). Thus, controlling for inequality reverses the unconditional results shown in Table 3.16 and Table 3.17, where LAC productivity growth was weaker and factor accumulation was stronger. We leave for future work the in-depth analysis of the links between inequality and the sources of growth.

3.6 Conclusion

The long-term growth performance of most countries in Latin America and the Caribbean has been poor. Output per capita growth has been unstable and low on average. By and large, LAC countries have grown more slowly than their peers around the world. Looking at the sources of the gap in output per capita growth relative to the rest of the world, we find that the shortfall is in TFP or productivity growth, rather than factor accumulation. The productivity growth gap accounts for almost all the overall growth gap. While the productivity growth gap shrank substantially after 1990, the same qualitative pattern remains true in most countries in this recent period.

We note that the level of TFP reflects not only technology use throughout an economy, but also the efficiency of resource allocation. In particular, misallocation of physical and human capital, both private and public, is reflected in a low level of TFP. Changes in the failures leading to resource misallocation thus directly impact TFP growth. Furthermore, resource misallocation may itself impede technology adoption and cause low TFP growth. Diagnosing the sources of the gap in productivity growth identified in this paper requires the consideration of resource misallocation and its drivers.

We have explored the association of inequality and growth to look at whether LAC's high inequality may account for the region's poor growth performance. We find that there is evidence that inequality is an important factor associated with the gap in long-term productivity growth and fully accounts for the post-1990 gap. Whether inequality is a proximate cause or an epiphenomenon, this observation is relevant for diagnosing LAC's sustained gap in productivity growth. Nevertheless, high inequality does not account for the shortfall in overall growth because it is also associated with a higher rate of factor accumulation.

References

- Barro, Robert J. (2000). “Inequality and Growth in a Panel of Countries”. *Journal of Economic Growth* 5.1. Publisher: Springer, pp. 5–32.
- Daude, Christian and Eduardo Fernández-Arias (Feb. 1, 2010). *On the Role of Productivity and Factor Accumulation in Economic Development in Latin America and the Caribbean*. SSRN Scholarly Paper ID 1817273. Rochester, NY: Social Science Research Network.
- Easterly, William and Ross Levine (Aug. 1, 2001). “What Have We Learned from a Decade of Empirical Research on Growth? It’s Not Factor Accumulation: Stylized Facts and Growth Models”. *World Bank Economic Review - WORLD BANK ECON REV* 15.
- Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer (Oct. 2015). “The Next Generation of the Penn World Table”. *American Economic Review* 105.10, pp. 3150–3182.

- Fernández-Arias, Eduardo and Sergio Rodríguez-Apolinar (May 1, 2016). *The Productivity Gap in Latin America: Lessons from 50 Years of Development*. SSRN Scholarly Paper ID 2956692. Rochester, NY: Social Science Research Network.
- Hsieh, Chang-Tai and Peter J. Klenow (2009). “Misallocation and Manufacturing TFP in China and India”. *The Quarterly Journal of Economics* 124.4. Publisher: Oxford University Press, pp. 1403–1448.
- Loayza, Norman, Pablo Fajnzylber, and Cesar Calderon (2005). *Economic Growth in Latin America and the Caribbean: Stylized Facts, Explanations, and Forecasts*. World Bank Publications. ISBN: 9780821360910. The World Bank.
- Ostry, Jonathan, Andrew Berg, and Charalambos Tsangarides (Jan. 1, 2014). “Redistribution, Inequality, and Growth”. *Revista de Economia Institucional* 16, pp. 53–81.
- Restuccia, Diego and Richard Rogerson (Oct. 1, 2008). “Policy distortions and aggregate productivity with heterogeneous establishments”. *Review of Economic Dynamics* 11.4, pp. 707–720.
- Solt, Frederick (2020). “Measuring Income Inequality Across Countries and Over Time: The Standardized World Income Inequality Database”. *Social Science Quarterly* 101.3, pp. 1183–1199.

Statistical Appendix

3.A Data

The data for the growth accounting (Sections 3.2–3.4) are from the Penn World Table, version 9.1.¹⁵ In all cases, output-based versions of real GDP are used because they are more suitable for the comparisons of productive capacity (as opposed to expenditure-based versions that are affected by trends in the terms of trade). The dataset for Section 3.5 includes inequality data of the Standardized World Income Inequality Database (SWIID), by Solt (2020).¹⁶ This includes consistently estimated series of the Gini index of disposable income.

3.A.1 Sample selection

Following Feenstra et al. 2015, we base our growth accounting exercises on the variable real GDP using national-account growth rates (RGDPNA), which is recommended

¹⁵See Feenstra et al. 2015; Penn World Table (database, version 9.10), Groningen Growth and Development Centre, Faculty of Economics and Business, University of Groningen, Groningen, the Netherlands, <https://www.rug.nl/ggdc/productivity/pwt/>.

¹⁶See Solt 2020; SWIID (Standardized World Income Inequality Database), Frederick Solt, Department of Political Science, University of Iowa, Iowa City, IA, <https://fsolt.org/swiid/>.

for studies comparing (output-based) growth rates across countries. TFP is the corresponding variable RTFPNA estimated in the Penn World Table. By contrast, output per capita with respect to the United States, utilized to measure the distance to the frontier at each point in time, is based on the variable output-side GDP at current purchasing power parities (CGDPo), which is recommended for comparisons of relative productive capacity across countries at a single point in time. TFP is the corresponding variable RTFPNA estimated in the Penn World Table. By contrast, output per capita with respect to the United States, utilized to measure the distance to the frontier at each point in time, is based on the variable output-side GDP at current purchasing power parities (CGDPo), which is recommended for comparisons of relative productive capacity across countries at a single point in time.

We put together a panel with annual information for 71 countries in 1961-2017 that are divided into the following groups:

- **(16) Latin America and the Caribbean (LAC):** Argentina, Barbados, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Jamaica, Mexico, Peru, Trinidad and Tobago, Uruguay, Venezuela
- **(55) Non-LAC economies**, divided into the following:
 - United States
 - (4) East Asian tigers: Hong Kong SAR, China; Republic of Korea; Singapore; and Taiwan, China

- (14) Africa: Burkina Faso, Cameroon, Côte d’Ivoire, Egypt, Kenya, Morocco, Mozambique, Niger, Nigeria, Senegal, South Africa, Tunisia, Tanzania, and Zimbabwe
- (36) Others: Australia, Austria, Belgium, Canada, China, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Luxembourg, Malaysia, Malta, the Netherlands, New Zealand, Norway, Philippines, Portugal, Romania, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Turkey, and the United Kingdom

For the analysis of inequality using the SWIID data has less historical coverage and includes only 65 countries (instead of 71), of which 14 are LAC countries: Argentina, Barbados, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Jamaica, Mexico, Peru, Trinidad and Tobago, and Uruguay.

3.B Construction of variables

The database was constructed as follows:

- Per capita variables are computed by dividing by population (variable POP), obtaining `rgdpnaPerCapita` and `cgdpPerCapita`.
- The per capita output distance measure to the United States for each country (`lcgdpPerCapitaUSA`) was constructed as the logarithm of the output per capita gap $\text{cgdpPerCapita}/\text{cgdpPerCapitaUSA}$ during the period.

- Annual growth rates are estimated considering log differences, to obtain $\text{lrgdpnaPerCapita_chg1}$ and lrtfpna_chg1 .
- Barbados; Burkina Faso; Cameroon; Côte d’Ivoire; Hong Kong SAR, China; Indonesia; Mozambique; Niger; Romania; Senegal; Singapore; Tunisia; and Tanzania had missing TFP data in the first years (before 1964). For these economies, the missing variable lrtfpna was estimated based on the predicted values of economy-specific regressions of lrtfpna_chg1 on $\text{lrgdpnaPerCapita_chg1}$ using the available sample for each country. We then extrapolated lrtfpna back to 1961 using the estimated growth rate.
- The non-TFP or overall factor accumulation contribution was obtained as a residual to account for per capita output growth purged from TFP: $\text{lrgdpnaPerCapita_chg1_nonTFP} = \text{lrgdpnaPerCapita_chg1} - \text{lrtfpna_chg1}$.
- The representative growth rate for each country grouping was obtained as a simple average of the growth rates of the corresponding countries.

To filter out the business cycle, the average of the annual growth rates during seven-year periods were considered with rolling windows (and assigned to pre- and post-1990 observations depending on where the window or most of it lay). For the purpose of sections 1 and 2, we considered fixed windows: 1962-68, 1969-1975, 1976-1982, 1983-1989, 1990-1996, 1997-2003, 2004-2010, and 2011-2017. The year 1990 divides the time span into equal parts, four subperiods before 1990 and four subperiods starting in 1990.