Firm Level Drivers of Productivity Growth

Bräuer, Richard

2021

VRIJE UNIVERSITEIT

FIRM LEVEL DRIVERS OF PRODUCTIVITY GROWTH

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad Doctor of Philosophy aan
de Vrije Universiteit Amsterdam,
op gezag van de rector magnificus
prof.dr. V. Subramaniam,
in het openbaar te verdedigen
ten overstaan van de promotiecommissie
van de School of Business and Economics
op maandag 10 mei 2021 om 15.45 uur
in de online bijeenkomst van de universiteit,
De Boelelaan 1105

door

Richard Bräuer

geboren te Gräfelfing, Duitsland

promotoren:	prof.dr. E.J. Bartelsman prof.dr. S. Müller

Contents

Acknowledgement

It turns out that economic theory is even relevant when writing economic theory: Agglomeration effects are everywhere and so this thesis has many more contributors than noted on the title page.

Foremost, I want to thank my supervisor Eric Bartelsman for his faith in the initial project, his encouragement and especially his many pointed questions and suggestions for improvement. Eric, when you read the first draft of the first chapter you said “I will keep an open mind” – I hope the final product at least partly vindicates your trust and that some of your inquisitive attitude and clean writing rubbed off, both for this project and the future.

To no lesser extent, I am indebted to my co-supervisor Steffen Müller for his support from the moment he hired me as a PhD student. His always insightful comments and insistence I broaden the scope of my studies are written all over this dissertation – especially obvious now that two thirds of it deal with (inventor) labor markets.

I also have to thank my coauthor, Matthias Mertens, for the countless hours spent discussing our paper, economics in general and the meaning of everything. I am lucky to have worked with you and I hope we will do so again in the future. I am also indebted to my coauthor Viktor Slavtchev, who supervised my first steps into economic research and whose exactness in empirical technique sharpened many a regression in this paper.

I am thankful for the many insightful discussions I was able to have with researchers at the IWH, at the VU, at the Nordic Econometric Meeting, at EGIT, at the Tinbergen Institute and KU Leuven about the papers enclosed in this dissertation.

Lastly, I would like to acknowledge my debt to my friends and family for enduring me talking about firm innovation way more than what is considered appropriate in polite company. Without your support and tolerance I could never have travelled the long and windy road that is a dissertation. A special thanks is in order to my wife Elsbeth for her willingness to read, reread and discuss unfinished chapters at any time between 6 in the morning and 4 also in the morning. Without your insistence to get this thing done, I would still be finishing the second chapter tomorrow!

Chapter 1

Introduction

1.1 Background

Over the last decades, productivity growth has been slowing down throughout developed economies. Since technology[1] growth is the main long-term determinant of productivity growth, this has ignited a debate about how new ideas are produced and disseminated through the economy. Differences between the growth performance of countries are largely explained by ICT capital and multifactor productivity (van Ark et al., 2008), again pointing towards technology as an important determinant of aggregate growth performance of the different countries. Increasing productivity growth again is a key policy objective: "Productivity isn't everything, but, in the long run, it is almost everything."[2] Slowing technology growth directly translates into lower incomes.

The matter is complicated by the measurement problems inherent in productivity analysis. As a "measure of our ignorance"[3], productivity is notoriously measured with error. Since many technological advances of the last decades are offered for free (e.g. internet services), at subsidized prices (e.g. ride sharing) or in public sectors (e.g. new drugs), they are poorly captured in GDP figures. Nonetheless, measurement error alone cannot explain most of the slowdown (Syverson, 2017; Cowen, 2011; Tarullo, 2014).

[1] As is standard in the literature, I subsume all knowledge about how to organize production processes under technology, i.e. better management techniques, better ways to motivate employees etc. all fall under this definition of technology.

[2] Krugman 1997.

[3] Abramovitz 1956.

While decelerating productivity growth is seen as a problem, the causes are hotly debated.

Techno-pessimists maintain that new ideas naturally become harder to find as the low hanging fruits are already picked. Since it is getting more difficult to make new discoveries, technology growth would naturally slow down over time (Gordon, 2016).

Another school of thought relates declining growth rates to slowing technology diffusion. In this reading, innovation progresses steadily, but diffuses through the economy more slowly. The "superstar firms" at the global frontier leave many firms behind. E.g. Autor et al. (2017); Akcigit and Ates (2019) argue that measured aggregate productivity growth is declining because fewer firms are using latest technologies.

Changes in competition could also slow down productivity growth. Aghion et al. (2005, 2006, 2009) show an inverted U-shape relationship between competition and innovation: Both monopolies and highly competitive markets are less innovative. The endogenous growth literature argues that this is because firms innovate to fend off competition and to increase their existing rents. Monopolists have no competition and thus do not need to defend themselves through innovation. Firms in a very competitive market have little incentive to innovate because they have many potential imitators and cannot expect to maintain their technology advantage for long. The optimum for innovation lies somewhere between these two points. De Loecker and Eeckhout (2017); Autor et al. (2017) present compelling evidence that competition has declined over the last decades and that firms' markups throughout the developed world have risen substantially. It might be that the global economy now has too little competition for innovation.

1.2 Research Approach and Key Findings

The papers collected in this dissertation bring microeconometric analysis to bear on these different explanations. I study the R&D and productivity reactions of German firms to increases in competition and the movement of inventors as a key determinant of technology diffusion. I thus examine the importance and plausibility of the suggested causes of the productivity growth decline. I also discuss the theoretical implications of sticky inventor firm relations on firms' research strategy and the equilibrium growth rate. To this end, I insert an inventor labor market into an endogenous growth model.

Chapter 2 studies the productivity responses of German manufacturing firms to increased foreign competition (2000-2014). We measure exogenous changes in the competitiveness of foreign firms by looking at their countries' market shares in third markets. We use this to instrument for the market share foreign firms capture in Germany. We study the effect of such changes in competition intensity on a whole range of firms' specific outcomes and find that German firms only increase their efficiency in response to competitors from other industrialized economies. This productivity increase is not driven by increased investment in innovation. Instead, firms cut back on costs while maintaining physical output. They also lower prices. In contrast, firms just shrink when confronted with competition from low cost countries like China. Overall, our evidence is more in line with firms cutting institutional fat when confronted with competition than with firms investing their "trapped factors" into R&D, as hypothesized by Bloom et al. (2016).

Chapter 3 studies the matching of inventors to firms on a global scale. I estimate inventors' and firms' contribution to patent production and analyze which inventors go to which firms. I find an increasing tendency for assortative matching, i.e. the best inventors are increasingly concentrated among the best firms. Patents are concentrated among few firms throughout the entirety of the data (1974-2012), but become even more concentrated during that time span. Additionally, inventors leave the most production efficient firms at declining rates, which might slow down technology diffusion. Inventors changing their movement behavior is not due to changes in the patent invention function, which is quite constant over time. Throughout the time period studied, inventor skill is more important for patent output than firm quality.

Chapter 4 synthesizes the empirical findings of chapter 3 into an endogenous growth model with inventor firm labor markets. Firms have to slowly build up a stock of inventors through search on the labor market. Thus, each firm has specific technological capabilities and firms with a large stock of inventors are invested into the specific technology their inventors have mastered. The most research heavy firms have the largest incentive to keep innovation incremental and the mapping of technologies to products stable. The trend towards more applied and less scientific innovations documented by Poege et al. (2019) is detrimental to growth, viewed through the lens of my model. The model thus suggests an alternative potential cause of slowing technology growth.

This research has been made possible by the proliferation of detailed firm level data sets and the computational and methodological resources to make use of them. Specifically, the literature on estimating firm level productivity with endogenous productivity allows to compare productivity across firms (Crepon et al., 1998; Bloom et al., 2016; Doraszelski and Jamandreu, 2013; De Loecker et al., 2016), while the labor market literature has developed tools to describe the matching of persons to firms (Abowd et al., 1999; Card et al., 2013). These techniques are central to the results reviewed above, though I have adapted and developed them further to fit the specific use cases presented.

1.3 Connection to the Wider Literature

Throughout this dissertation, I navigate an imperfect competition framework of firms' decision making. The empirical results can be understood in either a Hopenhayn (1992) type model with endogenous productivity or a quality ladder model like Aghion and Howitt (1992); Romer (1990). In both models, firms' contemporary profits depend on their current productivity and/or product quality. Firms can also undertake actions to increase their future productivity or product quality. Within this very general framework, several potential actions have been studied in more detail: the decision to enter foreign markets (Melitz, 2003), the decision to invest in R&D (Aghion, 1998), the decision to produce certain products (Khandelwal, 2010; Mayer et al., 2014) or the monitoring of firm managers (Leibenstein, 1966; Stigler, 1976). Our own empirical analysis does not presuppose any of the specific explanations these authors offer.

This dissertation is also closely related to the empirical literature on knowledge diffusion: Numerous studies have traced technology diffusion by studying patent data. Keller (2004) provides an overview over the different channels for cross country technology diffusion and argues that importing, FDI and own human capital and R&D are necessary for substantial absorption of foreign technology. The FDI channel specifically has received much scrutiny: While Potterie and Lichtenberg (2001) argue that technology mainly flows towards the FDI subsidiary using aggregate data, Fosfuri et al. (2001) show that technology spillovers arise when workers move from the foreign subsidiary to domestic firms. I will study this inventor movement channel of technology diffusion more generally.

An example of technology diffusion that has been studied in particular detail because of its importance to public policy is the proliferation of green technology. Bretschger et al. (2017) build a multi-sector, multi-country model where firms require both access to a "knowledge pool" of green production technologies for their sector and the "absorptive capacity" to understand the ideas flowing around between professionals. Comin and Mestieri (2018) demonstrate that technology penetration, i.e. firms' success in adopting new technologies, is diverging between countries, while information technology has closed the gap for early adopters. Aghion et al. (2016) show that previous knowledge in green vs. dirty technology makes a firm much more successful in absorbing new inventions: There is technology specialization and substantial path dependence. I will develop the argument that much of this path dependence is because firms' inventors are largely technology specialists and difficult to replace.

Chapter 2

Firms' Productivity Reaction to Competition

2.1 Introduction

One of the most fundamental tenets of economics is that competition promotes efficiency. Competitive pressure threatens firms' rents and even their existence. To escape competition, firms in theory take costly actions to improve their productivity (Aw et al., 2011; Aghion et al., 2005, 2004, 2009). Yet, there is only mixed empirical evidence for this mechanism: Bloom et al. (2016) find that public European firms increased their productivity and patenting in response to import competition from China, while Autor et al. (2016) find the opposite for the US. We also have little empirical evidence about how firms increase their productivity in response to competition (De Loecker and Goldberg, 2014; Shu and Steinwender, 2018).

To shed light on the effect of competition on productivity, we study if and how German manufacturing firms increase their productivity in response to import competition (2000-2014). To arrive at causal estimates, we exploit exogenous shocks from the world markets in the spirit of Autor et al. (2013): When foreign industries become more competitive in the world market, they pressure the domestic German market. We find that competition from low-income countries has no direct effect on firms' productivity. In contrast, competition from other high-income countries pressures German firms to improve their productivity. While other researchers have studied plant survival (Bernard et al., 2003), employee skill upgrading (Mion and Zhu, 2013) or innovation (Bloom et al., 2016; Autor et al., 2016), we document an effect of import competition on quantity based TFP. However, productivity only increases if the foreign competition is from other high-income countries. This is our main contribution.

We investigate how firms react to different competitors from around the world to understand how and why firms improve their TFPQ (productivity measured in physical output). Competitors from low-income countries present a different threat to German firms than competitors from similarly high-income economies: Low-income countries specialize in lower quality versions of goods (Khandelwal, 2010) and use more labor and less capital and technology in production (Schott, 2004; Hummels and Klenow, 2005). Our data reflects that: While we cannot observe the product quality of imports directly, we see that high-income countries threaten German products that are produced with more capital and R&D, while low-income countries are dominant in relatively labor intensive products. We find that these product quality differences of competitors induce the same German firms to react very differently to shocks from high or low-income countries.

When constructing our import competition measures and estimating TFP, we exploit the firm-product dimension of our data: Our product data allows us to estimate TFPQ in addition to TFPR. Since increases in competition change the price elasticity the firm faces, competition has a direct effect on firms' prices. Thus, revenue TFP will mechanically react negatively to competition, independent of productivity adjustments (De Loecker, 2011). We find that this effect changes the estimates substantially. We also use firms' product portfolios to calculate firm-specific competition measures. Using firms' product portfolios, we separate the effect of import competition from the effect of intermediate product imports and account for firms being active in several industries simultaneously. Thus, our data allows us to be more precise than previous attempts at measuring the effect of foreign competition on firm productivity (Autor et al., 2016; Bloom et al., 2016).

We use an IV strategy pioneered by Autor et al. (2013) to draw causal inferences: We can measure changes in the competitiveness of China, the US and other important German trading partners within third countries, which are independent of Germany. We isolate instances where Germany's trading partners become more competitive independently from German firms. We can thus instrument trade flows between Germany and its trading partners with trade flows between Germany's trading partners and a set of third countries.

Irrespective of the source of import competition, firms experience a drop in revenues and reduce their expenditures for production inputs. Firms respond to high-income import competition by reducing output prices and largely manage to keep their output quantities constant. Firms do not lower prices in response to competition from low-income countries and consequently experience a fall in sold quantities. It seems like German firms are unable to compete in terms of prices with product market competition from low-income countries. Notably, firms surviving competition from low-income countries invest in R&D. Firms' adjustment strategy to low-income import competition seems to be to escape by exploring new markets or inventing more efficient production technologies. In contrast, firms being hit by high-income import competition even decrease their R&D spending, presumably in an attempt to save costs. Overall, we conclude that the productivity enhancing effects of competition we document are not a consequence of increased R&D activities. Instead, they might result from "cutting fat", i.e. realizing existing unused potential to raise efficiency. Evidently, prior to the new competitors, firms' managers lived according to John Hicks: "The best of all monopoly profits is a quiet life."[1]

Firms might be inefficient either because management consumes a part of firms' rents as leisure (Biggerstaff et al., 2016) or because of true ignorance about better technology (Bloom and Van Reenen, 2010). Both hypotheses are consistent with our findings: New competitors from high-income countries introduce close substitutes to German firms' products into the market. As incumbents' demand curves flatten, inefficiency in general becomes costlier. Firms pick up on that and reduce their X-inefficiencies throughout the manufacturing sector. Such broad evidence was previously lacking. We supplement studies documenting such competition effects in narrowly defined sectors like health care (Bloom et al., 2015) or the oil industry after large world market price shocks (Borenstein and Farrell, 2000).

This paper complements the broad theoretical literature on the effects of international trade liberalization. Yet, the trade literature focuses mostly on productivity gains through selection (Melitz, 2003; Bernard et al., 2003; Melitz and Redding, 2013) and not within firm productivity effects. Our study relates more

[1] Hicks 1935.

closely to empirical work investigating how a relaxation of tariffs affects firm productivity and performance (Trefler, 2004; Bernard et al., 2006; Amiti and Konings, 2007; Khandelwal and Topalova, 2011). However, our focus is on firm-specific import competition rather than on a reduction of industry-wide tariffs. This allows us to clearly separate competition-based effects of international trade from other channels.

Additionally, our article relates to theoretical work on firm productivity (Aghion et al., 2004, 2005, 2009; Impullitti and Licandro, 2018). These models build around the idea that a firm's efforts to increase productivity are endogenous to competition. Aghion et al. (2009) show that competition within a specific product segment leads to more innovative activity when the technological distance between competitors is small, such that a successful innovation allows follower firms to leapfrog their competitors. In contrast, when the distance to the competitor becomes larger, the expected rents from innovation decrease, until eventually firms stop innovating. While we find that competition has productivity effects and that these depend on the new entrants, we cannot confirm that incumbents with different levels of technological sophistication react differently to the same entrant. In the data, the characteristics of the entrant determine the reaction. Our results thus better fit trade models like Khandelwal (2010), in which high and low-income countries have different modes of production and thus compete in different ways against each other.

However, our paper is most comparable to Autor et al. (2016) and Bloom et al. (2016). Both use the same identification idea to study firms' adjustment to increases in foreign competition. Our paper differs from their work in three ways: First, we paint a more complete picture of firms' responses to competition by considering different types of competition and including the variables through which firms increase their competition. Second, we address the bias inherent in estimating the effect of competition on revenue productivity. Third, we are able to measure import competition much more precisely due to our product level data. With these improvements, whenever we estimate comparable equations, our results are more similar to those of Bloom et al. (2016) than to those of Autor et al. (2016).

This paper is structured as follows: Section 2.2 introduces the data and explains the construction of our firm-specific import competition measures. Section 2.3

describes our procedure to recover a quantity-based firm-level productivity measure. Section 2.4 covers our econometric strategy to assess the impact of import competition on firm productivity. Section 2.5 presents our empirical results. Section 2.6 concludes.

2.2 Data and Measuring Import Competition

We use administrative yearly panel data on German manufacturing firms with at least 20 employees (AFiD thereafter) for the period 2000-2014. The German Federal Statistical Office and the Statistical Offices of the Länder jointly maintain AFiD. AFiD contains information on firms' production inputs and outputs, product portfolios, R&D expenditures and energy consumption. In principle, AFiD represents the entire universe of manufacturing firms with at least 20 employees. Yet, to limit the administrative burden, AFiD includes some variables only for a representative sub-sample encompassing roughly 40% of all firms. Intermediate input expenditures and employment by full time equivalents are only available for the sub-sample and are necessary to estimate firm TFP. As this sub-sample is stratified by industry and size-class, which are variables that we observe for all firms, we can construct inverse probability weights to translate all of our results to the underlying firm population.

Notably, AFiD provides detailed information on quantities and factory gate prices for the distinct final products produced by each firm at the nine-digit PRODCOM classification. This information is crucial for our study for two reasons: First, it allows us to control for firm-specific price variation when estimating firm productivity (see section 2.3). Second, it enables us to define import competition at the firm-level. Calculating import competition at the firm rather than the industry level accounts for firms being active in multiple industries simultaneously and allows us to clearly separate final product competition from competition in firms' supplier markets (i.e. intermediate input imports).

To construct a firm-specific measure for the strength of import competition, we combine the AFiD database with the United Nations Comtrade database (Comtrade thereafter) at the product-level. Comtrade contains the value and quantities of products traded between any two countries. After combining this product-level trade data with the product-level production data from AFiD, we calculate firm-level import competition as the revenue weighted share of imports in each firm's product markets:

$$IMP_{it}^{n} = \sum_{g} [\frac{R_{igt}}{\sum_g R_{igt}} \frac{M_{gt}^{n}}{M_{gt}^{World} + \sum_i R_{igt}}] * 100 \tag{2.1}$$

where g, i, and t respectively indicate the product, firm, and time dimension. M_{gt}^{n} is the value of all German imports of product g from a country(-group) n at time t. $\sum_i R_{igt}$ denotes the total German production value of product g (from firms with at least 20 employees), while R_{igt} and $\sum_g R_{igt}$ are a firm's sales of g and total product market revenue, respectively.

We calculate our import competition measure separately for a sample of high-income and low-income countries. Thus, we have: n=(High,Low), where we include USA, Canada, Japan, and South Korea into the high-income group and China, India, Russia, Brazil, South Africa, Argentina, Chile, Mexico, Malaysia, Turkey, Thailand, Tunisia, Bangladesh, Indonesia, Philippines, Vietnam, and Pakistan into the low-income group. We apply this separation because products from high- and low-income countries may differ in their characteristics with respect to product quality, capital intensity, level of unit costs of production, or embedded technology (Schott, 2004; Hummels and Klenow, 2005). By splitting import competition shocks from these two groups, we take into account that incumbents should react differently to different competitors. Incumbents might e.g. choose to compete over price or over quality. We discuss this further in our results section 2.5.

2.3 Estimating Firm Productivity

To recover a quantity-based measure of firm productivity (i.e. TFPQ), we define the following physical Cobb-Douglas production model:

$$Q_{it} = L_{it}^{\beta^l} K_{it}^{\beta^k} M_{it}^{\beta^m} \omega_{it} \varepsilon_{it} \tag{2.2}$$

where Q_{it} denotes produced quantity and L_{it}, K_{it}, and M_{it} respectively are the amount of labor, capital, and intermediates used in the production of Q_{it}. ω_{it} denotes Hicks-neutral total factor productivity and ε_{it} is an i.i.d. random error term that can represent both shocks in the real world and measurement error. Taking logs from equation (2.2) motivates estimating the production function as follows:

$$q_{it} = \beta^l l_{it} + \beta^k k_{it} + \beta^m m_{it} + \omega_{it} + \varepsilon_{it}, \tag{2.3}$$

where smaller letters denote logs and ε_{it} now is a standard linear error term. We aim to calculate ω_{it} as a residual after estimating the production function in equation (2.3). Before doing so, however, we need to address three econometric challenges.

First, due to differences in physical reporting units across products (e.g. volume vs. kilogram), we cannot define a quantity-based output measure for multi-product firms. To tackle this issue, we follow Eslava et al. (2004) and purge observed firm revenue from price variation by deflating it with a firm-specific price index calculated from information on product prices given in our data. Slightly abusing notation, we keep using q_{it} for the resulting quasi-quantities.

Second, we assume that the firm has to choose investment and labor before it learns its current productivity ω_{it}. This is justified, given the time it takes to install new machinery and the substantial rigidities of the German labor market (OECD, 2019). However, treating labor as a flexible input has negligible effects on our estimation results. Nevertheless, equation (2.3) cannot be estimated directly, as the firm chooses m_{it} based on the unobserved ω_{it}, which introduces endogeneity.

Third, although we observe labor inputs directly in quantities (i.e. in full time equivalents), capital and intermediate inputs are, by their nature, only reported in monetary units. Hence, after deflating k_{it} and m_{it} with sector-s-specific price indices, two unobserved terms capturing firm-specific deviations from industry-level prices enter our physical production model. Formally:

$$q_{it} = \beta^l l_{it} + \beta^k (k_i t + p^k_{it} - \bar{p}^k_{st}) + \beta^m (m_i t + p^m_{it} - \bar{p}^m_{st}) + \omega_{it} + \varepsilon_{it} \tag{2.4}$$

$$q_i t = \beta^l l_{it} + \beta^k \widetilde{k}_{it} + \beta^m \widetilde{m}_i t + \omega_{it} + \varepsilon_{it}, \tag{2.5}$$

where we define $\widetilde{k}_{it} = k_{it} + p^k_{it} - \bar{p}^k_{st}$, with the tilde indicating that the respective variable is deflated by an industry-level deflator. p^k_{it} and p^m_{it} respectively denote firm-level prices for capital and intermediate inputs and $\bar{p}^k_{st}$ and $\bar{p}^m_{st}$ refer to the associated industry-level price indices. As input prices are correlated with output volumes, estimating the above production function without observing p_{it}^k and p_{it}^m produces biased input coefficients (Beveren, 2012). To address this input price bias, we follow De Loecker et al. (2016). They show that under a number of assumptions, the price bias can be treated without observing input prices. These assumptions are

- differences in input prices across firms emerge from quality differences
- firms who manufacture high quality outputs do so by using high quality inputs
- complementarity in input quality, i.e. firms combine high quality labor with high quality intermediates
- vertical differentiation model of consumer demand

As discussed in De Loecker et al. (2016), those assumptions allow us to control for input price variation across firms using solely information on output prices. While they are restrictive, even more restrictive assumptions are made whenever researchers estimate production functions of multiproduct firms without explicitly treating the price bias in this way.

We act on this result. Specifically, for every firm we construct a revenue weighted average of the firm's product price deviations from the industry-wide average product prices for its various products. We denote this index by η_{it} and include it as an additional control variable into our production model:

$$q_{it} = \beta^l l_{it} + \beta^k \widetilde{k}_i t + \beta^m \widetilde{m}_i t + \gamma \eta_{it} + \omega_{it} + \varepsilon_{it}. \tag{2.6}$$

The last econometric issue we face is that ω_{it} is unobserved but correlated with firms' input decisions for flexible production inputs, i.e. with firms' input decision for intermediates. To solve this issue, we apply a control function approach in the spirit of Olley and Pakes (1996) and Levinsohn and Petrin (2003), where we derive an expression for ω_{it} from inverting firms' demand function for energy and raw materials (which are components of total intermediates), denoted by e_{it}:

$$\omega_{it} = g_{it}(.) = g_{it}(\widetilde{k}_{it}, l_{it}, \widetilde{e}_{it}, \mathbf{z}_{it}). \tag{2.7}$$

$\mathbf{z}_{it}$ captures state variables of the firm, which, in addition to capital and labor, influence firm productivity and the demand for e_{it}. As noted by De Loecker et al. (2016), $\mathbf{z}_{it}$ should be specified as broadly as possible. Therefore, we include dummy variables for export as well as research and development activities, dummy variables for the firm's headquarter location and its main four-digit industry, the number of products a firm produces, and firm-level import competition into $\mathbf{z}_{it}$. Assuming that ω_{it} follows a Markov-process, i.e. $\omega_{it} = \omega_{it-t} + \xi_{it}$, where ξ_{it} denotes the innovation in productivity, and plugging equation (2.7) into (2.6) gives:

$$q_{it} = \beta^l l_{it} + \beta^k \widetilde{k_i} t + \beta^m \widetilde{m}_i t + \gamma \eta_{it} + g_{it-1}(.) + \xi_{it} + \varepsilon_{it} \tag{2.8}$$

which constitutes the basis of our estimation. We estimate equation (2.8) in one step following Wooldridge (2009) and instrument $\widetilde{m}_i t$ and η_{it} with their lags to allow for productivity shocks to affect those flexible variables. Hence, the identifying moments are given by:

$$E(\xi_i t + \varepsilon_i t | l_i t, \widetilde{k}_{it}, \widetilde{m}_{it-1}, l_{it-1}, \widetilde{k}_{it-1}, \widetilde{e}_{it-1}, \mathbf{z}_{it-1}, \Gamma_{it-1}, \eta_{it-1}) = 0 \tag{2.9}$$

where Γ_{it} collects interaction terms entering $g_{it}(.)$. Having estimated the production function, we can recover firm productivity by:

$$\omega_{it} = q_{it} - (\beta^l l_{it} + \beta^k \widetilde{k}_{it} + \beta^m \widetilde{m}_{it} + \gamma \eta_{it}).$$

To allow for differences in production technologies across sectors, we estimate equation (2.9) separately for every NACE rev. 1.1 two-digit sector with at least 500 observations. Table 2.1 presents the associated results.

Overall, our estimates look reasonable with returns to scale being mostly close to one. Output elasticities vary considerably across industries, highlighting the importance of allowing for differences in production technologies across industries. Note that output elasticities for capital are less precisely estimated than output elasticities for intermediates and labor, which is in line with existing work, e.g. De Loecker et al. (2016); Dhyne et al. (2017). For industries 27, 29, and 35 we even estimate negative values for capital's output elasticity. As such estimates are inconsistent with our production model, we exclude those sectors from further analysis.

Table 2.1: Output Elasticities by Sector

Sector		# obs (1)	m (2)	l (3)	c (4)	RTS (5)
15	Food products & beverages	16,566	0.68***	0.22***	0.16***	1.05
			(0.02)	(0.02)	(0.04)	
17	Textiles	3,925	0.76***	0.25***	0.01	1.02
			(0.03)	(0.04)	(0.04)	
18	Apparel, dressing etc.	1,367	0.77***	0.18***	0.04	0.99
			(0.03)	(0.04)	(0.05)	
19	Leather & leather products	778	0.75***	0.22***	0.12	1.08
			(0.04)	(0.05)	(0.09)	
20	Wood & wood products	2,850	0.70***	0.25***	0.01	0.96
			(0.03)	(0.04)	(0.05)	
21	Pulp & paper products	3,618	0.81***	0.18***	0.03	1.02
			(0.03)	(0.04)	(0.02)	
24	Chemical products	7,030	0.76***	0.22***	0.06	1.05
			(0.02)	(0.04)	(0.04)	
25	Plastic products	7,835	0.69***	0.10	0.04	0.83
			(0.03)	(0.08)	(0.03)	
26	Non-metallic minerals	6,747	0.74***	0.26***	0.02	1.02
			(0.02)	(0.03)	(0.03)	
27	Basic metals	5,213	0.72***	0.27***	-0.01	0.98
			(0.03)	(0.04)	(0.03)	
28	Fabricated metal products	12,944	0.70***	0.27***	0.08**	1.04
			(0.02)	(0.05)	(0.03)	
29	Machinery & equipment	14,564	0.73***	0.13***	-0.04	0.82
			(0.02)	(0.04)	(0.03)	
30	Electronics & optics	631	0.82***	0.21***	0.28**	1.31
			(0.09)	(0.09)	(0.13)	
31	Electrical machinery	5,402	0.68***	0.26***	0.10***	1.05
			(0.03)	(0.04)	(0.04)	
32	Television & communication	1,257	0.77***	0.04	0.12	0.93
			(0.05)	(0.11)	(0.12)	
33	Precision instruments	3,279	0.61***	0.23***	0.11	0.96
			(0.03)	(0.05)	(0.08)	
34	Motor vehicles	2,881	0.81***	0.15***	0.04	1.00
			(0.07)	(0.05)	(0.06)	
35	Transport equipment	8,15	0.78***	0.07	-0.35**	0.50
			(0.07)	(0.08)	(0.11)	
36	Furniture manufacturing	4,287	0.75***	0.17***	0.04	0.96
			(0.03)	(0.05)	(0.04)	

Notes: Results obtained from equation (2.6) per sector. Columns 1-5 report the number of observations, the output elasticities for intermediate, labor, and capital inputs and the returns to scale. All regressions control for time dummies and are weighted using inverse probability weights. Clustering at the firm-level. Significance: *10 %, **5 %, ***1 %.

Table 2.2: Firm Productivity with and without Price Variation

		TFPQ		TFPR	
		Mean	SD	Mean	SD
	Sector	(1)	(2)	(3)	(4)
15	Food products and beverages	2.20	0.23	2.83	0.16
17	Textiles	2.97	0.21	3.22	0.14
18	Apparel, dressing, and dyeing of fur	2.62	0.18	2.54	0.13
19	Leather and leather products	1.73	0.19	2.50	0.12
20	Wood and wood products	3.98	0.22	3.24	0.12
21	Pulp, paper, and paper products	2.18	0.20	2.99	0.12
24	Chemicals and chemical products	2.41	0.24	2.50	0.15
25	Rubber and plastic products	4.38	0.32	3.73	0.13
26	Other non-metallic mineral products	3.25	0.23	3.41	0.14
28	Fabricated metal products	2.83	0.26	3.25	0.14
30	Electrical and optical equipment	-1.91	0.54	0.74	0.42
31	Electrical machinery and apparatus	2.71	0.27	2.67	0.17
32	Radio, television, and communication	2.29	0.31	2.37	0.23
33	Medical and precision instruments	3.83	0.27	5.83	0.29
34	Motor vehicles and trailers	2.07	0.21	3.27	0.15
36	Furniture manufacturing	3.06	0.24	2.66	0.16

Notes: This table reports estimates of firm productivity. Columns 1 and 2 refer to quantity-based TFP measures, whereas columns 3 and 4 report statistics for TFP when ignoring firm-level price variation when estimating the production function. Columns 1 and 3 report means. Columns 2 and 4 report standard deviations.

Table 2.2 shows estimates of our quantity-based productivity measure, to which we refer as TFPQ, next to a productivity measure that ignores price variation across firms within industries, which we call TFPR. To estimate TFPR, we deflate firm revenues with a sector-level deflator and omit η_{it} from equations (2.6)-(2.9). While we find only minor differences between our TFPQ and TFPR measures in some sectors (e.g. industries 18, 24, and 31), other industries display huge discrepancies between both productivity measures (e.g. sector 30, 33, and 34). Note that the dispersion in TFPR is smaller than in TFPQ, which is in line with findings in Foster et al. (2008).

2.4 Identifying the Productivity Effects of Import Competition

To assess the effect of import competition on firm productivity, we estimate a fixed effects model:

$$\omega_i t = \beta^{High} IMP_{it-1}^{High} + \beta^{Low} IMP_{it-1}^{Low} + C_{it-1}^{\prime}\gamma + \theta_t + \theta_{is} \tag{2.10}$$

where $C_{it-1}^{\prime}$ is a vector of control variables capturing firms' export intensity and number of products. θ_t and θ_{is} are time and interacted firm-sector fixed effects, respectively. Controlling for firm-sector fixed effects eliminates the potential for statistical jumps in firm productivity due to changes in firms' sector classification (as the parameters of the production function are estimated separately for individual industries). We thus identify our coefficients using within-firm-within-sector variation. In essence, our regression model is similar to a first difference model but avoids a disproportional loss of observations when working with a rotating panel (as in our case). We weight all observations using inverse probability weights to achieve a representative estimate and lag our import competition variables to allow for a time span of adjustment that is consistent with our production model.

However, there are valid endogeneity concerns when estimating equation (2.10) by OLS, which prohibit any causal interpretation of our results. There are two main concerns:

1. Foreign competitors might specifically target unproductive firms and sectors, which causes reverse causality.

2. Domestic German governments might protect specific sectors and firms from foreign competition, most likely especially uncompetitive sectors.

To solve this endogeneity problem, we apply an instrumental variable strategy following Autor et al. (2013) and Dauth et al. (2014). Specially, we exploit that an increase in the competitiveness of a country-group n induces supply shocks also for other countries besides Germany. Using trade flows between German competitors and third countries therefore allows us to isolate changes in a country's competitiveness that are unrelated to German policy changes or the particular weakness of German firms. To implement the IV strategy, we instrument our import competition measures with the share of country-group n's imports in total imports of product g observed in third countries. Hence, we define firm-level instruments for country-group n's import competition as:

$$IS_{it}^{n \to third} = \sum_{g} [\frac{R_{igt}}{\sum_g R_{igt}} \frac{M_{gt}^{n \to third}}{M_{gt}^{World \to third}}] * 100 \qquad (2.11)$$

where $M_{gt}^{n \to third}$ is the value of product g imports flowing from n to third countries. As for our endogenous import competition measure, we aggregate product-level trade flows for our instruments to the firm-level by using revenue weights.

A crucial point for our IV strategy to work is that there are no other unobserved confounding factors that are correlated between Germany and countries included in the instrument country-group (e.g. correlated demand and supply shocks or monetary policy within the European Monetary Union). This would violate our exclusion restriction. Besides that, our instruments must be relevant enough to avoid a weak instrument problem. Therefore, we follow Dauth et al. (2014) and include countries with an income level similar to Germany in our instrument country-group, except for all direct neighbors of Germany and members of the European Monetary Union. Ultimately, our third country-group consists of Norway, New Zealand, Israel, Australia, Great Britain, Sweden, and Singapore.

Note that the weighting scheme we use to aggregate product-level trade flows to the firm-level might introduce another endogeneity problem when firms adjust their product-mix in anticipation of import competition. In a robustness check, we therefore use a more rigorous specification where we base our aggregation of product trade flows for our instruments on constant weights using firms' first observed product portfolio (the product-level data already starts in 1995, 5 years before the start of our TFP series). This eliminates the potential for any endogenous product mix adjustment by firms.

2.5 Results

2.5.1 Import Competition and Firm TFP

Table 2.3 shows results from estimating equation (2.10) by OLS and IV. Given that OLS suffers from the multiple endogeneity problems discussed above, we only interpret the IV results. For a first overview, we pool import competition from all countries. We find that a one percentage point increase in total import competition causes an increase in firm productivity by 0.2%.

Table 2.3: Firm Productivity and Import Competition

	OLS	IV
	ω_{it}	ω_{it}
	(1)	(2)
$IMP_{it-1}^{High+Low}$	-0.0001	0.0018***
	(0.0004)	(0.0001)
Firm Controls	YES	YES
Firm * sector FE	YES	YES
Time FE	YES	YES
Observations	78,414	78,414
R-squared	0.986	0.986
First-stage F-test	-	142.00
Number of firms	16,925	16,925

Notes: This table reports results from estimating equation (2.10) by OLS (column 1) and IV (column 2) when pooling import competition from high- and low-income countries. All regressions are weighted using inverse probability weights and include controls for firms' export intensity and number of products. Standard errors are clustered at the firm-level. Significance: *10 percent, **5 percent, ***1 percent.

In several theoretical frameworks, a firm's reaction to new competition depends on the type of the competitor: In a quality ladder model in the vein of Romer (1990); Aghion and Howitt (1992), the technological distance between incumbent and new competitor determines both the size and sign of the response. Since competition might force firms to innovate in order to escape their competitors, but also erode the rents which finance innovation, the substitutability between the incumbent's and the entrant's product is also a key determinant of the response (Khandelwal, 2010; Aghion et al., 2006; Aw et al., 2011). Both arguments can be applied in our setup: Goods from low-income countries are typically characterized by lower unit costs of production and lower quality levels (Schott, 2004; Hummels and Klenow, 2005) than German goods. The quality of imported goods is not observed directly, but we can show that imports from high-income countries disproportionally go to sectors of the German economy that use comparatively little labor, but more capital and R&D. The reverse is true for low-income countries (Appendix A). We thus are comfortable to suggest that holding the product code constant, there are substantial differences in product quality and technological sophistication between products from high- and low-income countries. Thus, from a German firm's point of view, import competition from a low-wage country (as China) may pose a completely different threat than import competition from a high-wage country (as the US). Table 2.4 separates total import competition into import competition from high- and low-income countries (as described by equation (2.10)).

Table 2.4: Firm Productivity and Import Competition

	OLS	IV	IV	IV	IV
	ω_{it}	ω_{it}	ω_{it}	ω_{it}	ω_{it}
$IMP^{High}_{(it-1)}$	0.0004	0.0112***	0.0222***	0.0206**	
	(0.0009)	(0.0037)	(0.00713)	(0.0104)	
$IMP^{Low}_{(it-1)}$	-0.0003	-0.0005	-0.0008	0.0001	
	(0.0005)	(0.0010)	(0.00148)	(0.0018)	
$IMP^{High}_{(it-1)}$ (only core)					0.0165*
					(0.0100)
$IMP^{Low}_{(it-1)}$ (only core)					-0.0093
					(0.0068)
$IMP^{High}_{(it-1)}$ (non-core)					-0.0053
					(0.0074)
$IMP^{Low}_{(it-1)}$ (non-core)					0.0080
					(0.0071)
Firm * sector FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
First portfolios	NO	NO	YES	NO	YES
Single-product firms	NO	NO	NO	YES	NO
Observations	78,414	78,414	73,212	22,729	45,559
R-squared	0.986	0.985	0.984	0.982	0.983
First-stage F-test	-	36.89	13.13	12.09	3.38
Number of firms	16,925	16,925	15,853	5,467	9,690

Notes: Table 2.4 reports results from estimating equation (2.10) by OLS and IV when separating import competition into high- and low-income country import competition. Columns 1 and 2 respectively show OLS and IV results from our baseline specification using all available firms. Column 3 uses firms' first observed product mix to aggregate product-level trade flows to the firm-level for the instrument variables. Column 4 runs our baseline specification exclusively for single-product firms. All regressions are weighted using inverse probability weights and include controls for firms' export intensity and number of products. Standard errors are clustered at the firm-level. Significance: *10 percent, **5 percent, ***1 percent.

The OLS estimator is again inconclusive (column 1). Using our IV specification, we find that the positive productivity effect of import competition is solely driven by high-income countries (column 2). This strong result implies that firms only become more productive in response to threats from comparable competitors, while ignoring low-income competition.

There are two threats to the IV identification used in column 2. The first threat is that firms anticipate changes in competition and adjust their product portfolio before the shock. Thus, firms might self-select into treatment by dropping or entering exposed markets. As discussed in section 2.4, we construct our instrument using firms' first observed product portfolio to alleviate this concern. Column 3 shows that the measured effects are even stronger when accounting for this potential problem. This suggests that if at all, firms move away from attacked products and our baseline methodology is thus biased downwards.

The second threat is that different countries attack different parts of firms' product portfolio. If low-income countries only attack firms' peripheral products, we might not measure a response because firms do not care about these products, independent of who competes with them. We gauge the scope of this problem by estimating equation (2.10) for single-product firms only (column 4) and by estimating two coefficients for import competition in core and non-core products (column 5). We still find that high-income countries are solely responsible for productivity gains.

As accounting for both potential identification problems leads to higher point estimates, we view our main specification as a conservative baseline.

Still, there are three different interpretations:

1. First, high- and low-income countries compete with different German firms and these different German firms react differently.

2. Second, high- and low-income countries enter different sectors of the German economy and competition in these different markets works differently.

3. Third, high- and low-income countries might produce different versions of the same product, which leads to different responses by German firms.

Both interpretation (1) and (2) require that high- and low-income countries target different firms. Table A.2 in appendix A shows that low-income countries indeed target products with lower capital and R&D intensity. However, only a minority of firms (15%-20%) are overwhelmingly exposed to either one type of competition. Most firms are affected by comparable levels of threat from both high- and low-income countries. I.e., most markets are characterized by the simultaneous existence of alternatives from low-income countries, domestic German firms and high-income countries. We thus conclude that the most likely driver of the estimated effect differences is (3): Goods from high- and low-income countries are viewed as different products by consumers and thus domestic German firms react differently to their introduction.

To confirm this interpretation, we split the firms into groups according to whether they primarily faced competition from low-income countries and according to their lagged productivity. This allows us to check whether firms with different characteristics exhibit the same response. To conduct this analysis, we interact import competition with an indicator variable for each group. Table (2.5) reports the results from this regression.

Table 2.5: Productivity Effects in Different Groups of Firms

	Firms Exposed to Low-Income Competition		Productive Firms	
	OLS	IV	OLS	IV
	ω_{it}	ω_{it}	ω_{it}	ω_{it}
$IMP^{High}_{(it-1)}$	0.0039**	0.0209***	-0.0006	0.0098*
	(0.0020)	(0.0059)	(0.0012)	(0.0050)
$IMP^{Low}_{(it-1)}$	-0.0004	-0.0005	0.0000	-0.0002
	(0.0006)	(0.0010)	(0.0006)	(0.0011)
$IMP^{High}_{(it-1)} * D_{(it-1)}(medium)$	-0.0039*	-0.0097*	0.000146	0.0000
	(0.0020)	(0.0054)	(0.000822)	(0.0013)
$IMP^{Low}_{(it-1)} * D_{(it-1)}(medium)$	0.0011	0.0001	0.0002	-0.0002
	(0.0011)	(0.0029)	(0.0003)	(0.0004)
$IMP^{High}_{(it-1)} * D_{(it-1)}(negligible)$	-0.0038*	-0.0083	0.0009	0.0012
	(0.0022)	(0.0068)	(0.00111)	(0.00173)
$IMP^{Low}_{(it-1)} * D_{(it-1)}(negligible)$	-0.0035	-0.0202	-0.000312	-0.0008
	(0.0056)	0.0173	(0.000456)	(0.0006)
Firm * sector FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
$D_{(it-1)}(group)$	YES	YES	YES	YES
Observations	78,353	78,353	68,982	68,982
R-squared	0.986	0.985	0.987	0.986
First-stage F-test	-	4.938	-	8.429
Number of firms	16,911	16,911	14,493	14,493

Notes: Table 2.5 reports results from estimating equation (2.10) by OLS and IV when separating import competition into high- and low-income country import competition. To rule out that our effects are only driven by high- and low-income competition hitting different firms, this table presents results after splitting firms along their relative exposure to low-income trade and productivity. Highly exposed firms or highly productive firms form the baseline. Firms that experienced at least three times as much low-income import competition as high-income competition are coded as highly exposed. The medium category contains firms with roughly equal levels of exposure or a foreign market share lower than 5%. Firms with negligible low-income competition exposure are firms that have at least three times as much high-income competition than low-income competition. For productivity, firms are grouped into tertiles according to last year's productivity. The results show that firms react very similarly and firms exposed to low-income competition are, if at all, more sensitive to shocks. Thus, our results cannot be driven by which firms were shocked. All regressions are weighted using inverse probability weights and include controls for firms' export intensity and number of products and interaction terms of these variables with the group dummies. Standard errors are clustered at the firm-level. Significance: *10 percent, **5 percent, ***1 percent.

Firms mostly attacked from low-income countries form the baseline category in column 2 of Table 2.5. Such firms are actually the most sensitive to competition pressure of all types, as is evident from the negative interaction terms. Thus, while firms exposed primarily to low-income competition do not encounter high-income country competitors often, if they do, they actually react about twice as sensitive as the average firm. They are also the only firms to react at least somewhat to competition from low-income countries, increasing their productivity by about 0.4% per percentage point rise in the market share of low-income competitors. However, because of how few firms are exposed to only one type of competition, the differences between the three groups are barely significant.
The most productive third of firms forms the baseline category in column 4 of Table 2.5. However, these firms do not act differently than their less productive counterparts. This is in contradiction to quality ladder models, where the most productive firms act differently than other incumbents, especially to technologically advanced entrants. This result also holds when splitting firms by research intensity (share of R&D in total costs).

2.5.2 Import Competition and Firm Adjustments

Of course, firms cannot directly choose their productivity levels. To better understand the strikingly different effects of competition from different countries, we study the adjustment strategies of firms. Specifically, we analyze the effects of import competition on firms' sales, quantities, prices, input decisions, and R&D expenditures. Table 2.6 reports the associated results, where $\widetilde{r}_{it}$, P_{it}, q_{it}, l_{it}, w_{it}, $\widetilde{k}_{it}$, $\widetilde{m}_{it}$, and $log(R\&D_{it})$ respectively refer to the firms' revenue, output price index, quasi-quantities, full-time equivalents, wage bill, capital stock, intermediate expenditures, and logged R&D expenditures. Again, smaller letters denote logs. Note that we focus on the intensive margin of R&D spending by using logged R&D expenditures as dependent variable.

Regardless of its origin, we find that foreign competition affects firm sales negatively (column 1 of Table 2.6). This assures us that firms are adversely affected by our competition measures. In case of high-income import competition, the reduction in sales is driven by a fall in output prices, whereas firms being hit by low-income import competition reduce their produced quantities. Evidently, firms join into a fierce price competition over market shares with competitors from high-income countries, while they simply resign market shares to low-income competitors.

Next, we analyze how firms adjust their input decisions (columns 4, 5, 6, and 7 of Table 2.6). Low-income import competition causes firms to reduce their employment and input expenditures. Although firms exposed to high-income import competition also decrease their input expenditures, they do not reduce their employment levels. This discrepancy between wage and employment adjustments can be a consequence of firms passing through adverse effects of competition to their employees by lowering wages and/or of firms reorganizing their workforce (i.e. churning).

Firms have a completely different long-term strategy in response to the distinct types of competition: We find that surviving firms faced with competition from low-income countries increase their R&D spending, presumably in an attempt to upscale their products or to discover a different market. Although we do not find any direct positive effects of low-income import competition on firm productivity, this increase in R&D activities suggests a potential for future productivity gains that are not yet realized one year after an import competition shock. This finding is in line with Bloom et al. (2016), but we cannot corroborate their positive effect of competition from China on productivity. In contrast, R&D spending in firms facing competition from high-income countries seems to be victimized by the same cost saving impulses as other expenditures.

An important implication of this latter finding is that R&D investments cannot explain the increase in productivity from high-income import competition. Instead, high-income import competition increases firm productivity by forcing a more efficient use of production inputs that translates into a reduction in total input expenditures while keeping output quantities constant. This is likely associated with a reduction in so-called X-inefficiencies within firms (Leibenstein, 1966; Stigler, 1976).

Such X-inefficiencies are often seen as a form of rent consumption by non-shareholders (Biggerstaff et al., 2016). If this is true, then fiercer competition increases the price of this consumption. Theoretically, as demand curves become flatter, small differences in productivity can lead to hugely different profit outcomes. Consequently, tighter competition will force firms to monitor their production processes (and employees) more strictly. Since high-income competition erodes the firms' (monopoly) rents, we interpret our findings as cross-industry causal evidence for this behavior, something that was previously lacking, though a number of specialized studies exist (Borenstein and Farrell, 2000; Bloom et al., 2015).

Table 2.6: Firm Adjustment and Import Competition

	$\widetilde{r}_{it}$	q_{it}	P_{it}	l_{it}
IMP^{High}_{it-1}	-0.0129*	0.0010	-0.0065*	-0.0052
	(0.0068)	(0.0067)	(0.0036)	(0.0041)
IMP^{Low}_{it-1}	-0.0060***	-0.0059***	0.0008	-0.0031**
	(0.0021)	(0.0023)	(0.0011)	(0.0014)
Firm * sector FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	78,414	78,414	78,414	78,414
R-squared	0.987	0.985	0.836	0.985
First-stage F-test	36.89	36.89	36.89	36.89
Number of firms	16,925	16,925	16,925	16,925
	w_{it}	$\widetilde{k}_{it}$	$\widetilde{m}_{it}$	$log(R\&D_{it})$
	-0.0097**	-0.0099*	-0.0131*	-0.0870***
	(0.0047)	(0.0060)	(0.0073)	(0.0317)
	-0.0035**	-0.0029**	-0.0062***	0.0314**
	(0.0014)	(0.0015)	(0.0022)	(0.0154)
Firm * sector FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	78,414	78,414	78,414	26,544
R-squared	0.989	0.992	0.986	0.909
First-stage F-test	36.89	36.89	36.89	17.55
Number of firms	16,925	16,925	16,925	5,305

Notes: This table reports results from estimating equation (2.10) by IV. The dependent variable in columns 1-8 is respectively a firm's logged revenue, logged produced quasi-quantity, output price index, logged full time equivalents, logged wage bill, logged capital stock, logged intermediate input expenditures, and logged R&D expenditures. All regressions are weighted using inverse probability weights and include controls for firms' export intensity and number of products. Standard errors are clustered at the firm-level. Significance: *10 percent, **5 percent, ***1 percent.

2.6 Conclusion

This study analyzes how import competition affects firm productivity. To address our research questions, we rely on a comprehensive administrative data set on German manufacturing sector firms containing price and quantity information on firms' final products. Based on that data, we derive a quantity-based productivity measure that isolates changes in firms' technical efficiency from changes in firms' output prices, which is necessary since competition has a direct effect on prices.

We split import competition according to country of origin and find that firms react differently to competition from high- and low-income countries. The positive effect of competition on German firms' productivity is solely driven by competition from high-income countries: Faced with competition from low-income countries, the same firms do not improve their productivity.

To better understand our main result, we also document how firms achieve the productivity improvements that we find. Import competition from high-income countries leads to strong reductions in inputs (employment, wages, intermediate inputs and capital), but to essentially no decline in physical output. Instead, firms facing competition from high-income countries lower their prices. Firms facing competition from low-income countries do not lower their prices and lose more market share. Their TFPQ thus does not increase, they just become smaller. However, firms increase their R&D in response to competition from low-income countries. This increase in R&D expenditures might translate into long-run productivity improvements that we do not capture in our empirical specification.

We argue that the documented productivity gains can only be explained if firms are not operating at their maximum efficiency level. There is compelling evidence that firms exhibit sizeable slack, which explains a large part of the observed productivity dispersion between firms (Bloom et al., 2012). For instance, firms' managers might consume a part of their firms' profits as leisure (Biggerstaff et al., 2016). Theoretically, competition should exert pressure towards efficiency. Empirically, this has so far only been shown in highly specific cases for select industries (Borenstein and Farrell, 2000; Bloom et al., 2015). Our study provides

the first empirical cross-industry evidence that firms have potential for additional productivity gains. Whether or not they use this potential depends on the type of competition they face.
We arrive at causal results by isolating exogenous increases of competitiveness of German trading partners through markets in third countries, following Autor et al. (2013). However, since we determine competition not at the sector-level, but at the product-level, we can measure it much more precisely and isolate the effect of competition from the effects of cheaper intermediate inputs.

Our results on innovation confirm the findings of Bloom et al. (2016), who showed that European firms innovated in response to trade competition from China. They are contrary to Autor et al. (2016), who demonstrated that US firms reduced their R&D efforts. Our findings best fit a model in the vein of Khandelwal (2010), where new competitors from similar countries pose a stronger threat to domestic incumbents because they produce products of similar quality and technological sophistication. Quality ladder type endogenous growth models predict that higher productivity or more research intensive firms should react differently to competition, which we cannot find in the data.

Chapter 3

Firms' and Inventors' Matching Behavior

3.1 Introduction

I analyze a potential cause of the productivity growth slowdown in advanced economies, namely a change in the patterns of allocation of research talent across firms. Using the PATSTAT patent data base, I find evidence of an increasing tendency for assortative matching from 1974-2012 on a global scale: Good inventors increasingly match with firms with high quality research departments. These companies hoard inventive talent.

The gains from this assortative matching have been small: Average patent arrival rates have been largely stable throughout this period. The estimated patent arrival rate of inventor-firm pairs puts less weight on the firm: Marginally increasing firm quality increases the patent arrival rate by half as much as increasing inventor skill. The patent invention function is largely stable over time and thus cannot explain the changed matching behavior.

To analyze whether inventor mobility is a potential channel of technology diffusion, I link patents to firm level data (AMADEUS 2000-2010) and find that the share of inventors leaving high productivity firms for low productivity firms declines. Firms' own patents and an inflow of inventors from other firms increase productivity and boost profits. These findings suggest that increased assortative matching of inventors to firms is a plausible driver of the slowdown in technology diffusion. Conversely, since any match a firm secures with the inventors of new technologies is sticky, matches serve as natural imitation protection: Firms themselves report that staff retention and technological lead are their most important strategies for securing the profits from their inventions. Comparatively, patents only play a minor role (Harhoff, 1997). Yet, while some work exists on which inventors match with which firms (Pearce, 2019a), matching between skill levels is understudied: To my knowledge, I present the first application of labor market matching estimators that can recover inventor skill and firm quality to inventor-firm relations. In other settings, however, the literature on labor market matching has already documented increased assortative matching (Abowd et al., 1999; Card et al., 2013; Andrews et al., 2008; Hagedorn et al., 2017).

Rising assortative matching of skilled inventors to high quality firms and slowing technology diffusion might explain a substantial part of the productivity growth slowdown of the last decades: The literature on the economy during the productivity growth slowdown has documented declining labor shares (Autor et al., 2017), increased profit shares (Barkai, 2017) and increased markups (De Loecker and Eeckhout, 2017). Rising market concentration is often seen as a result of technological leadership by superstar firms (Autor et al., 2017). Theoretically, slowing technology diffusion can explain productivity growth decreases and increased concentration simultaneously (Helpman and Trajtenberg, 1998; Bresnahan and Trajtenberg, 1995). Empirically, diffusion slowdowns have indeed been linked to productivity growth declines with diverse empirical strategies (Gal, 2017; Comin and Mestieri, 2010). Akcigit and Ates (2019) combine the two approaches and calibrate a standard endogenous growth model to show that declining technology diffusion can fit slowing productivity growth, rising markups and other trends in the US economy in the past decades.

To arrive at the empirical results, I adapt a state of the art labor market matching estimator (Hagedorn et al., 2017) to be usable for linked inventor-firm patent data. I make two methodological contributions: First, I can show how one can substitute wages used in the original estimator with patenting performance. Second, I develop a technique to deal with the fact that inventor-firm matches are not observed in years without patent applications. Specifically, I recover the underlying unobserved joint distribution of employment tenure and patent arrival rate through maximum likelihood estimation and use it to estimate the duration and productivity of each match.

Both Hagedorn et al. (2017) and my adaptation draw from the theoretical literature on matching in the labor market, reaching back to Mortensen and Pissarides (1994). We both use this theory to inform the empirical literature concerned with the matching of workers of different ability to heterogeneous firms, following Abowd et al. (1999). The empirical literature has found that high ability workers tend to sort to successful firms and finds a trend towards this assortative matching (Mendes et al., 2010; Card et al., 2013).

I adapt Hagedorn et al. (2017) instead of other estimators intended for the same purpose: Lamadon et al. (2015); Bonhomme et al. (2017); Lentz et al. (2018) have less theoretical foundation and higher data requirements. This is because they rely on grouping similar firms (or workers) based on additional variables. Unfortunately, PATSTAT contains little information on both inventors and firms besides their patents, so it is difficult to group similar workers and firms with accuracy.

I use the PATSTAT data base provided by the EPO because of its global coverage.[1] PATSTAT contains inventor and firm names and rich information on the content of the patent, up to the original document. PATSTAT can be used as a matched employer-employee data set after extensive data treatment, for which I improve upon Magerman et al. (2006) and Peeters et al. (2010). The final data contains information on the output of each inventor-firm pair in each year. However, only pairs contributing to at least one patent are observed. I account for this truncation by estimating the Poisson rate of patenting for each employment spell via maximum likelihood estimation. This yields the probability to observe any given employment spell and get an unbiased estimate of its duration and expected number of patents per year.

[1] I exclude communist countries before 1988 since both the function and size of firms are not comparable to market economies.

The remainder of the paper is structured as follows: Section 3.2 will describe the data and my treatment of it. Section 3.3 will present the estimation procedure. Section 3.4 will present and discuss the results. Section 3.5 concludes.

3.2 Data

3.2.1 The PATSTAT Data

Patent data from across the world gathered in the PATSTAT database forms the basis of my empirical strategy. This data contains the filing date of any patent application, a description of the technology and the names of firms and inventors involved. For some participating countries, the data starts in 1850, however, coverage pre-WW2 is generally low. Patents from some countries are only available from a later date onwards: E.g., Japan enters the database in the mid-seventies. Around the same time, coverage rates improve in general and the data can give a reliable picture of worldwide patent activity.
The following graph shows the number of patents over time for selected countries. Note that the stable or shrinking number of national patents for EU countries is offset by a large increase in EU-wide EPO applications.

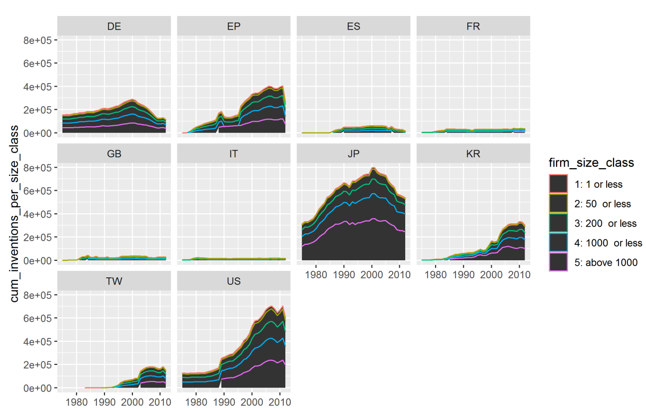

Figure 3.1: Patent applications per patenting authority; DE = Germany; EP = European Patent Office; ES = Spain; FR = France; GB = Great Britain; IT = Italy; JP = Japan; KR = Republic of Korea; TW = Taiwan; US = USA. Source: PATSTAT

Peruzzi et al. (2014) provide a PATSTAT-AMADEUS link, which I use to relate my inventor labor market data to actual economic outcomes like profits or firm TFPR. Apart from string matching firm names, they use the other variables in AMADEUS to predict which firms are more likely active in PATSTAT. Their technique allows to merge around 140.000 companies to the PATSTAT database.

Using PATSTAT as an employer-employee data set entails challenges as well as advantages over commonly used social security data. The following gives a brief overview over the main opportunities and problems when using this data, compared to standard social security employer-employee data sets. A detailed description of the necessary data treatment steps can be found in Appendix E.
The first advantage of PATSTAT is that it is much richer than social security data regarding the type of work that inventors do: Patent applications contain descriptions of the technology and a list of co-inventors. In employer-employee settings, all workers are usually treated as perfect substitutes, only differentiated by the skill with which they produce. I improve upon this treatment by using the IPC 4-digit technology codes assigned to every patent: I contract the technology space into 56 technology clusters, comprised of IPC classes that often appear jointly on patent applications. I use the clustering algorithm of Pons and Latapy (2005). Throughout the rest of the paper, technological clusters will differentiate inventors horizontally, i.e. there will be separate labor markets and rankings in each technology cluster. Inventors are assigned to their main technology cluster. Inventors' patent portfolios are largely within one technology cluster: The most important technology cluster of an inventor covers 88% of his patents on average and 56% of inventors only patent within one cluster.
Second, PATSTAT's patents are a direct measure of the output of a match between firm and inventor, which is usually not available from employer-employee data. Since this data is normally derived from social security declarations, output is approximated using wage information. However, the wage also contains the bargaining position of both parties, which makes it difficult to extract match production.
Third, most workers, including inventors, work in teams. Such worker teams are not observable in standard matched employer-employee data sets. However, PATSTAT's patent applications contain the names of all contributing inventors.

I will discuss in section 3.2.2 which assumptions create an incentive to form teams and how such teams affect the matching rationale of firms and inventors. I will also provide some evidence on which assumption is supported by the data.

However, PATSTAT data is not originally intended as an employer-employee data set and using it this way also entails some challenges. Importantly, PATSTAT does not contain unique firm or person identifiers. Instead, it contains the names as written into the fields "inventor" and "applicant" on the patent. Thus, an important step whenever using PATSTAT is to identify individuals and firms, for which I improve upon earlier works (Peeters et al., 2010; Magerman et al., 2006) with a multi-step procedure.
This leaves the problem of one name representing multiple inventors. So far, there is little systematic treatment of this possibility. I use name frequency tables, IPC class portfolios of the alleged inventors and the longevity of alleged inventors to find names likely representing more than one inventor and drop them from the data.

After these cleaning procedures, which I detail in Appendix E, I feel confident when interpreting the remaining data as an employer-employee data set which contains both the inventors and the firms involved in any patent.

3.2.2 Patent Contents and Inventor Teams

PATSTAT contains information about the actual content of inventions through patents' technology classes. I use patents' technology classes to extract information about which inventors do similar research and could in principle be substituted. This defines the size of inventors' labor markets. While current search and matching labor market papers treat the whole labor market as one, I split the labor market for inventors into different markets for different technology clusters and propose an algorithm which can be transferred to a more standard setting, should more data on workers' occupation become available. Intuitively, the algorithm clusters technologies between which inventors switch frequently, because this indicates that these inventors are substitutable. Appendix F details the proposed algorithm, which treats each category combination as a potential distinct cluster and then connects such clusters where possible.

PATSTAT also contains information about the team structure in the form of co-signers on patent applications. Inventor teams offer a fundamental challenge: There is neither a theoretical model nor a readily available estimator for a situation where workers are hired and then assigned to teams. The current state of the art estimators treat the output of a worker as a function of his skill and the firm's quality only, assuming that all workers work independently from each other.

In the larger literature, there are two different ways to explain why inventor teams form.
Akcigit et al. (2018) exemplify the first way. Inventor teams create patents according to a Cobb-Douglas production function in the team leader's skill and the number of inventors: $\lambda = (x_i)^{\zeta} n^{(1-\zeta)}$. Only the skill of the team leader matters, so mediocre inventors can make a meaningful contribution if they are paired with an excellent inventor. Beyond this one example, this first way of modeling assumes that inventors are in principle substitutable, but that grouping them increases the arrival rate of patents.
The opposite approach is to maintain that inventors are complements: Each inventor possesses unique knowledge. Inventors work together because some research projects require knowledge in multiple areas and one inventor cannot master them all. E.g. Pearce (2019b) studies how inventor teams form and how the returns of more depth (teams with deeper expertise of one area) and width (teams with expertise in different fields) have changed over time, relative to inventors performing research alone.

Even before ranking inventors, the raw data can offer some guidance as to which modeling approach is more appropriate for this particular data set.
First, the size of inventor teams is largely independent of firm size: Inventors are organized in teams of 2-4 inventors, no matter how large the firm is (figure 3.2).

Second, inventors with a high patenting output work in teams with other inventors with many patents. Sorting all inventors by the number of patent families they partook in is of course an imperfect measure of skill, since it ignores the contribution of firms. However, the correlation is strikingly high (figure 3.3).

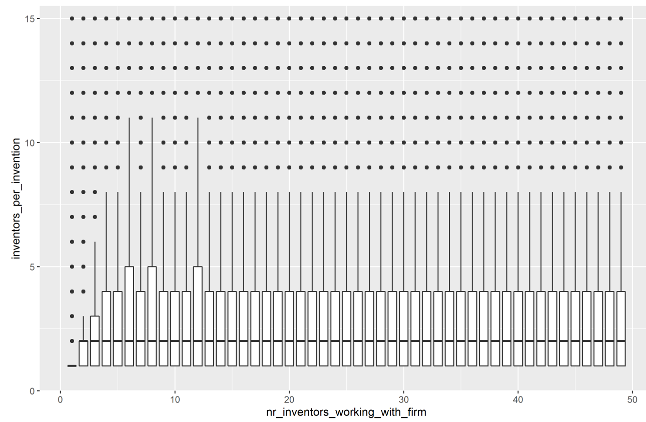

Figure 3.2: Boxplot of the team size per patent family, sorted by the number of inventors working for the same firm. Firms of basically all sizes opt for teams of 2-4 inventors. Larger firms do not generally assemble larger teams. Even firms too small to form teams of three inventors often do so by cooperating with other firms.

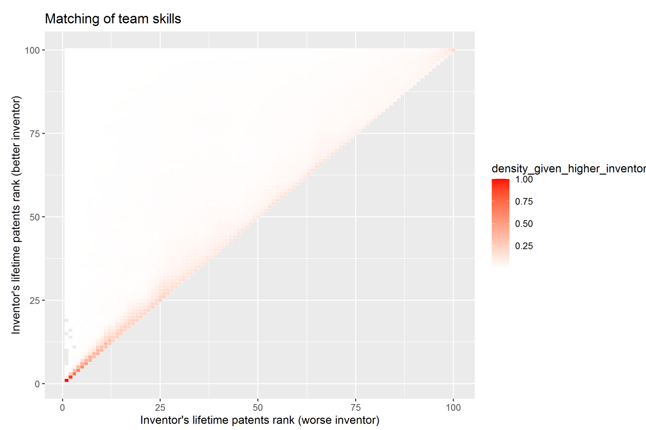

Figure 3.3: The graph shows the quality of the two inventors in a team. Both axes rank all inventors by the number of patent families they contributed to. 100 is the inventor who participated in most patent families. The x-axis denotes the rank of the less prolific inventor in any two person team, while the y-axis denotes the rank of the better inventor. The density of matches is highest along the diagonal. If the better inventor is in the 100% percentile, his co-inventor is likely to also be in the top percentile. The same holds true across all percentiles: Prolific inventors match with good co-inventors, unproductive inventors match with unproductive co-inventors. Matching a star inventor to a helper seems to be less common.

Third, patent families created by large teams span more patent classes and teams with more than three inventors span more than two technology clusters on average. One explanation for this pattern is that larger teams form to tackle projects with a broader scope than what any one inventor could cover (Figure 3.4).

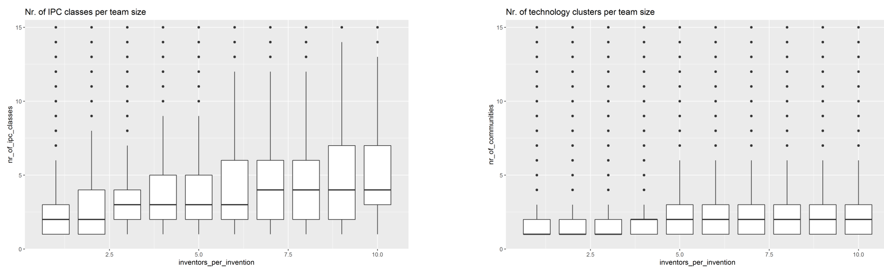

Figure 3.4: The left graph reports box plots for the number of full length IPC classes (70.000 different classes) per patent family in relation to how many different inventors contributed to the patents of the family. Smaller inventor teams produce patent families with fewer IPC classes. The right graph reports the same statistic, but for technology clusters. Inventors are assigned to one technology cluster, but larger teams produce patents with IPC classes from two or more technology clusters.

These data points are more compatible with some models than with others. First, the fact that firms of all sizes form teams of the same size is not compatible with significant within-firm matching: If firms searched for compatible inventors to form teams with, larger firms would use their larger pool to find better matches and build larger teams. Instead, marginal productivity seems to decline with team size, just as in Akcigit et al. (2018).
Second, teams consisting of two frequently patenting inventors are not rationalizable with the specific patent invention function of Akcigit et al. (2018): With their production function, high-skilled inventors should form teams with low-skilled helpers. Instead, inventor skill levels within a team seem to be complements, not substitutes.
Third, larger inventor teams produce patent families which span more IPC classes and technology clusters. This is in line with a model in which inventors with different knowledge band together to tackle projects that span multiple areas of expertise.

Overhauling the whole labor market matching theory to include collaborative projects is outside the scope of this paper. However, the theoretical model presented in the next chapter will at least loosen the assumption that inventors' output is strictly independent from each other without losing tractability. This opens up the possibility that future work can tackle team formation in a search and matching context. In addition, the empirical section will discuss how matching complementary inventors affects standard estimators.

3.2.3 Estimating the Duration of Matches

An additional challenge when using patent data is that inventors are missing from the data if they do not patent in any given year. The data is thus truncated, since any combinations of inventor and firm not patenting in a certain year are not observed. Even very productive inventors are only observed with a probability of roughly 50-70%.[2] Thus, match productivity and the time the match existed have to be estimated.

Estimating an arrival rate for events when the underlying population is not observed is a problem that goes beyond this particular paper. Other use cases are e.g. publications, complaints at government agencies, legal cases at court and trademarks. In all of these applications, only "active" units of observation show up in the data. The arrival rate could be learned from the untruncated data, but this might not exist or be unavailable due to confidentiality issues. The methodological contribution of this part of the paper is to demonstrate how to solve the truncation problem present in such data with weak assumptions.

In the patent literature, some studies try to link patent and census data, which faces its own problems and is not always even theoretically possible. Other studies make the ad hoc assumption that inventors work for the same firm between observations. This in itself does not allow to consistently estimate the arrival rate of patents, since the years before the first and after the last patent are still missing.

The estimation I propose requires two assumptions:

[2]Estimated patent arrival rates are between 0.2 and 1 (see Appendix G).

1. Inventors continue to work at the same firm between observations.

2. The arrival rate of patenting events is constant for a given match between firm and inventor.

These assumptions are enough to recover all parameters of interest. Any potential estimator to recover firm and worker ability makes assumption 2 anyway (Hagedorn et al., 2017). Extensions where the arrival rate evolves over time according to a known function follow naturally from the approach presented, but are unnecessary for this specific paper. The weak assumptions necessary to correct for truncations facilitate the transfer of this correction technique to other settings.
The central approach of the estimation is to understand the original, untruncated data as a mixture distribution of different types of employment spells, characterized by their length and the arrival rate of patenting events. This underlying distribution creates a distribution of observable outcomes, like an observed spell of a patent followed by two years of non-patenting, followed by another patent (1001). The estimated underlying distribution of spell types is the one that produces a distribution of observable outcomes close to the one in the data. Given this estimate, it is easy to estimate patent arrival rate and length for every observed spell. The details of how to derive this estimate are described in Appendix G.

Figure (3.5) shows the results of the correction. It shows the difference between a "naive" treatment of the data, where the truncation issue is just ignored, and the corrected data. Each arrow shows how observed spells were moved in the productivity-length plane: In the bottom left corner, I estimate that spells where only one patent in one year was observed have on average an underlying productivity of just 0.15 patents per year and last roughly 8 years. If one does not take into account the missing zeros, one would overestimate the productivity in these employment spells. For extremely long spells (15 years or more), the estimator even increases the productivity of some spells compared to the naive baseline. This is because it takes into account that long spells with a mediocre productivity would in some cases show up as unproductive. While this is an interesting implication, these estimates do not matter much quantitatively, because

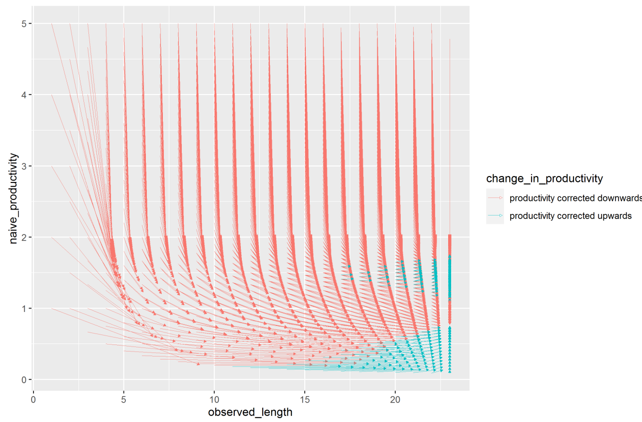

Figure 3.5: Adjustment of observed employment spell productivity and length. The starting point of each arrow is the productivity and length observed in the data without the correction routine. The end point of each arrow gives the new estimated arrival rate of patents after the routine has concluded. Red highlights spells where the observed productivity was adjusted downwards, blue highlights spells where the observed productivity was adjusted upwards.

few spells are actually that long.

As is intuitive, the GMM routine estimates that productivity is much lower than a naive reading of the data might suggest. This is because it includes completely unsuccessful years in the productivity estimate. Additionally, the GMM graph is much flatter: The routine concludes that while inventors in longer spells are generally more productive, the difference is much less pronounced. This is because the truncation correction takes into account that long matches with low productivity often generate only one or two patents and thus look just like short spells in the data. Long and short employment spells are less different than one would conclude at first glance.

After this correction technique, the data can be treated as an employer-employee data set which for each match contains

- the estimated length
- the estimated start and end date
- the number of patent families the match participated in
- the estimated arrival rate of patenting events

- the number of co-inventors for each realized patenting event

- expected match output $\lambda_{x,y}$ as arrival rate times the inverse of the expected number of co-inventors

While I have to adapt standard labor market matching techniques, they are transferable to this new setting.

3.3 Estimation Framework

This section details the framework within which I estimate firm quality and inventor skills. The central assumption in the labor market matching literature is that output is produced by matches of workers and firms. In the context of this paper, inventors invent in conjunction with the firm they work for. The arrival rate of new inventions is a function of the inventor's skill and the quality of the firm's research environment, or firm quality for short. Firms' quality y and inventors' skill x are unknown to the econometrician but known to some actors in the economy, as is the patent invention function $\lambda(x, y)$. The goal of the econometrician is to estimate these objects.
There are two main challenges when transferring standard labor market estimators to this setting. The first challenge is that standard estimators expect a continuous wage variable, measured with reasonable precision. Instead, patent data contains the discrete number of patents an inventor has applied for. Even taking citations into account, the outcome variable is measured with non-normal error. The second challenge is showing that an estimation procedure accurately ranks inventors and firms when given patent-per-year instead of wages. Specifically, I demonstrate that my estimator yields unbiased inventor and firm rankings even if the patent invention function $\lambda(x, y)$ changes over time or the production function is not logarithmic.

3.3.1 Ranking with Large, Non-Normal Measurement Error

The problem resulting from large measurement error becomes apparent when looking at an example: Consider four inventors A, B, C and D. They work for two different firms, X and Z. Figure 3.6 shows the matching between inventors and firms and the resulting patent invention rates. C and D have the same patent invention rate of 50% a year. However, they will likely not have the same outcome in the data: If the firm produces the expected number of patents, only one of them will be successful. Thus, a naive ranking according to their outcome would produce much higher skill diversion within the firm than is actually the case.

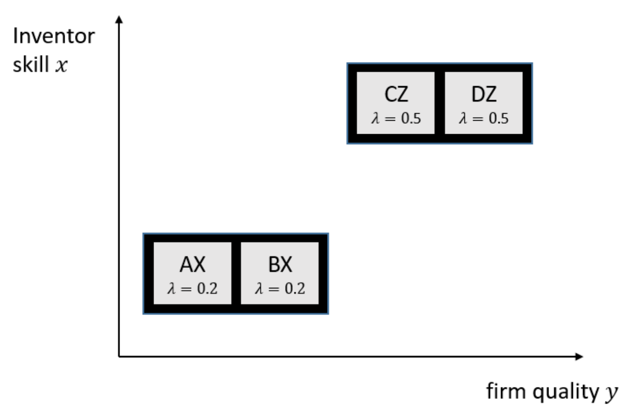

Figure 3.6: Example of inventor-firm matching. Inventors A and B have both matched with firm X and both produce 0.2 patents per year. Hence, they both have the same skill. Inventors C and D have both matched with firm Z and both produce 0.5 patents per year. This is due to both inventors having higher skill than A and B and firm Z being of higher quality than firm X.

Importantly, even ideal data would not alleviate measurement error in the rate of patent inventions. Ideal data would contain the employment biographies of inventors, a designation that marks when they are assigned to research activities and the patenting outcomes. However, even such data would only imperfectly measure the patenting productivity of inventors: Patenting is a rare event and even perfect data will contain enough measurement error to make rankings suspect. Any study of the patent invention function has to solve this problem, regardless of estimation technique and data sources.

Measurement error in spell productivity will affect the results in two main ways. First, it will bias the estimate for assortative matching towards 0: Even if a high quality firm only works with high quality inventors, some matches will be unlucky and look unproductive. Likewise, unproductive matches of low quality firms with low quality inventors will sometimes seem really productive.
Second, measurement error will make inventor skill look more important than it really is: Because inventors usually have few spells, their patent arrival rate is measured with even more error than the average arrival rate of (large) firms. Thus, any estimator will pick up on the fact that inventors at the same firm have widely different outcomes and conclude that inventor skill is an important driver of patenting.
The size of the bias can be substantial: In the simulation exercise described in Appendix H with an unadjusted (Hagedorn et al., 2017) estimator, measurement error in λ reduced estimated assortative matching by half (0.4 instead of 0.8) and twisted the production function from $\lambda_{y_f,x_i} = y_f * x_i$ to $\lambda_{y_f,x_i} \approx x_i$, i.e. the estimator was unable to detect any significant effect of firm quality.
In the example of the four inventors above, consider a potential observed outcome for the matches in figure 3.7. On average, half of the inventors in both firms will produce more and half will produce less patents than expected. The econometrician observes these $\hat{\lambda}$ and would conclude that assortative matching is weak and inventors' skills are an important driver of match productivity differences.

I use a Maximum Likelihood argument to correct for this problem: I search for the distribution of match productivities that is most likely to produce the observed data. To compute this probability, one needs the global joint distribution of employment length and patenting probabilities, i.e. how many spells of which type there are in the data set. I estimate this distribution anyway, in order to correct for the truncation problem of only patenting matches being observed 3.2.3, but the reasoning is flexible enough to incorporate any estimation technique that yields this joint distribution. In the best case, with untruncated data, the econometrician can just observe this distribution. In the example, the truncation correction procedure would conclude that two employment spells had a patent arrival rate of 0.2 and two spells had a patent arrival rate of 0.5. With this additional information, there are two possible scenarios that could have produced

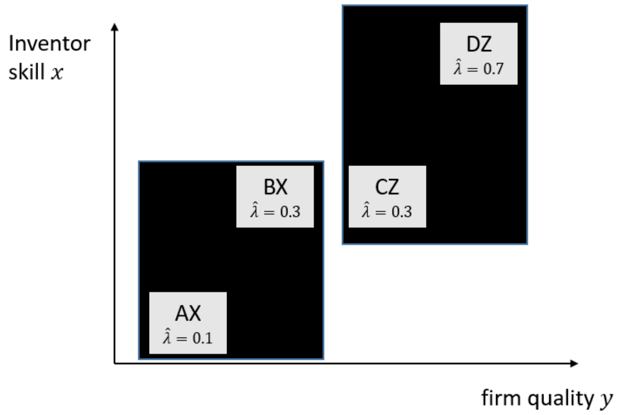

Figure 3.7: Example of inventor-firm matching. The econometrician does not observe the original patent arrival rate λ, but $\hat{\lambda}$, which is measured with error. Half of the inventors in both firms produced more patents than expected, the other half produced less. If taken at face value, the econometrician would overestimate the difference between the inventors in both firms and underestimate the degree of sorting.

the observed distribution (Figure 3.8).

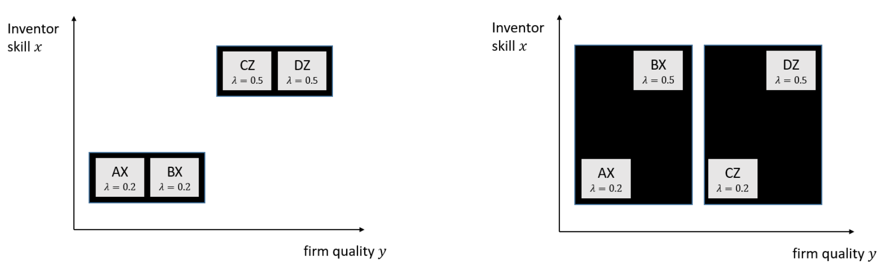

Figure 3.8: Two different scenarios that both conform to the overall distribution of spells (two with 0.2 and two with 0.5), but have drastically different implications for the estimated production function and assortative matching. The likelihood of the observed data is lower if the right scenario is correct, so it is discarded. If the right scenario was correct, all four matches had to draw exactly the productivities observed. In contrast, in the left case, either match at one of the two firms could have over- or underperformed and the result would have been indistinguishable from the observed data.

Between these two possibilities, the left scenario in Figure 3.8 is much more likely: In it, each firm has on average the expected number of patents. In the other case, one firm consistently overperformed and the other firm consistently

underperformed. Ideally, I would like to compute the Maximum Likelihood for every possible distribution of "true" productivities among the observed spells in this way. However, with millions of spells, this is not feasible. Instead, I use a pruning algorithm that randomly draws possible true productivities for each spell and then consecutively eliminates the most unlikely draws.
To check the performance and robustness of my empirical findings, I undertook a simulation exercise described in more detail in Appendix H. This exercise corroborates that the algorithm is able to identify the correct distribution of match productivity and the correlation between firm and inventor skill. However, the estimate for any individual inventor is still subject to substantial error, especially if they match only with few firms. In the above example, the Maximum Likelihood technique would conclude that both firms matched with inventors of the same skill level and could thus provide a correct estimate for every inventor. However, if firms match with inventors with different skill levels who do not move to other firms, the individual skill estimates are subject to substantial error.

3.3.2 Potential Estimators

If the measurement error is taken care of, the problem of how to extract rankings from the observed inventor-firm pairings remains. Abowd et al. (1999) proposed a two way fixed effects estimator to capture firms' and inventors' contribution to wages. Transferred to patent data, they propose to estimate

$$ln(\lambda_{x,y}) = y_f + x_i + u_t \tag{3.1}$$

where $ln(\lambda_{x,y})$ is the natural logarithm of the number of patents per year, y_f is a firm fixed effect and x_i is an inventor fixed effect. This estimates firm quality and inventor skills, but also assumes a specific, constant patent invention function. Using this estimator and substituting patent production for wages is problematic: A long strand of techno-pessimist literature maintains that ideas are becoming harder to find over time (Gordon, 2016), which would imply a changing patenting invention function. Additionally, the framework makes it difficult to analyze which inventors are matching with which firms: A low estimate for a firm's quality will automatically increase the skill estimate for all of its workers, since both have to add up to the (log) expected number of patents in equation (3.1). Correcting for this estimation error is nontrivial and existing methods (Andrews et al., 2012; Gaure, 2014) cannot account for the non-symmetric error introduced by the truncation of the data. Transferring the estimator to the patent production function at least eliminates the implication of irrational wage bargaining that is inherent in the above specification (Hagedorn et al., 2017). Nonetheless, this does not offset the disadvantages above.

Lamadon et al. (2015); Bonhomme et al. (2017); Lentz et al. (2018) all build on Abowd et al. (1999). They allow for more complex relationships between output and inventor skills by additionally estimating the probability of inventors moving from one firm to the next. However, these approaches require enough additional variables to plausibly proxy the attractiveness of firms and inventors for each other. Such information is not available in my setting. Their applicability also suffers from the fact that I cannot definitively determine the start of an inventor's working life in the patent data.

Another strand of the literature has a more structural approach: Since search and matching labor markets are well understood in theory following the seminal work by Mortensen and Pissarides (1994), one can use theoretical results in the estimation. This of course assumes that the theoretical model is a reasonable approximation of reality. Hagedorn et al. (2017) propose that agents behave according to a quite general search and matching model of the labor market. The implications of optimal behavior in this class of models allow them to identify workers' and firms' types independently and before estimating the production function. I adapt the HLM approach to my quite different data and aims.

An important difference between PATSTAT and the employer-employee data used by Hagedorn et al. (2017) is that they observe wages while PATSTAT contains direct information on output. In addition, I allow for a changing search technology and patent invention function.

3.3.3 Ranking Inventors within a Dynamic Search and Matching Labor Market

I recover a skill ranking of all inventors from their theoretically optimal behavior. In standard matching models, firms create vacancies and look for workers, while workers search for jobs. The rate at which matches are formed depends on the number of firms and workers searching. Whenever a firm and a worker meet, they reveal their types, decide whether to match or keep searching, and Nash bargain over the wage. A match is formed whenever there is a match surplus, i.e. the production of the match is high enough to pay both parties at least their outside option, which is to continue searching. The decision which partners to accept for a match is the central decision in the model.

In the inventor-firm setup, the match output are patents. Thus, firms value matched inventors as a stream of future patents, which will entitle them to a stream of future profits. In continuous time, the value of a match for the firm can be expressed as

$$r * V_y(x,y) = [V(p)\lambda(x,y) - r(V_u(x) + V_v(y))](1-\alpha) - \delta * V_y(x,y) + (1-\delta)\dot{V}_y(x,y) \tag{3.2}$$

The first term denotes the surplus value of the match: The output of the match (value of a patent $V(p)$ times its patent arrival rate $\lambda(x,y)$) minus the payout streams from an empty vacancy for the firm ($r * V_v(y)$) and unemployment for the inventor ($r * V_u(x)$). The two sides match whenever the output of the match is more valuable than if both parties just continued searching. The second term denotes the threat that the match is severed exogenously (e.g. because the inventor has to move or dies). In this case, the firm loses the match but gains the value of an empty vacancy $V_v(y,t)$. The last term denotes the value change of the match due to changing surroundings, given that the match survives. This term is treated as zero, since the economy is assumed to be in steady state.

In order to make this direct transfer more suitable for a patent setting, I assume that

1. the patent invention function is dependent on the year the match was formed $\lambda(x,y,t_{start})$. This allows for inventions becoming harder to find or cross fertilized by the technology level in other fields.

2. the search technology is dependent on the year, so that the probability of finding a new match is ρ_t.

This changes the above equation to

$$\begin{aligned} r * V_y(x,y,t) = (V(p)\lambda(x,y,t_{start}) - (r * V_u(x,t) + r * V_v(y,t)))(1-\alpha) \\ - \delta * (V_y(x,y,t) - V_v(y,t)) + (1-\delta)\dot{V}_y(x,y,t) \quad (3.3) \end{aligned}$$

Note that the value of unemployment, a vacancy and a match are now time dependent. The value of vacancies is time dependent since both the probability of finding potential matches and the productivity of any accepted match change over time.

Despite these complications, within firm and time, employees can be ranked according to their output. This is a direct consequence of assuming that all workers have a cardinal ability: Workers with a higher ability can expect to perform better than their colleagues at any firm, even if the difference might be smaller or larger at different firms. Mathematically, $\frac{\partial\lambda(x,y,t_{start})}{\partial x} > 0$ by assumption. Therefore, among all matches starting at the same time at the same firm, more skilled inventors have a higher expected output. Conversely, ranking inventors by their realized output within each firm is also ranking them according to their skill (albeit with noise, since realized and expected output are not the same). This yields numerous inventor rankings (one within each firm in each time period), which might be partially in disagreement with each other.

Assuming only vertical differentiation is of course problematic, but this assumption is made throughout the literature (Hagedorn et al., 2017; Abowd et al., 1999; Andrews et al., 2012). Compared to these studies, I relax this assumption significantly. I split the whole inventor labor market into smaller markets concentrated on specific technology clusters and assume solely vertical differentiation only within each sub-market. Using 56 technology clusters constructed from the co-assignments of IPC classes to patents (Appendix E), I allow for much more horizontal differentiation than usual in studies of this kind.

Yet, the rankings within firms are possibly not enough to define a global ranking: Consider a situation where inventors only move within two groups of firms, but never across. In this case, within firm rankings would not be informative about which of these two groups of inventors is more skilled than the other: Since they are never at the same firm, the two groups of inventors cannot be compared. Just like a double fixed effects estimator, the within firm ranking based method requires connected sets.

The theoretical framework offers additional avenues to rank inventors and connect the sets of within firm rankings. First, the value of unemployment at any point in time is rising in inventor skill for the same reason it is rising in the original model: A more skilled inventor can always exactly replicate the search and matching strategy of a less skilled one, but produce more output and receive a higher wage. A symmetrical argument can be made from the viewpoint of the firm, so the value of a vacancy behaves similarly ($\frac{\partial V_u(x,t)}{\partial x} = \frac{\partial V_v(y,t)}{\partial y} > 0$). While $V_u(x,t)$ and $V_v(y,t)$ are of course unobserved, they are by definition equivalent to the expected discounted lifetime earnings of a worker.

However, from this it does not necessarily follow that the inventor's skill is increasing in lifetime productivity. If the patent invention function is not super modular, an inventor might earn more by matching with low quality firms, because good inventors can extract high wages in these matches. This introduces a negative relationship between high output and high wages and might cause the expected patent output to be falling in inventor quality. Thus, the derivation will only work if the production does not exhibit strongly negative supermodularity. Labor market matching seems to be assortative across very different estimation techniques, data sets and applications (Abowd et al., 1999; Andrews et al., 2008; Borovičková and Shimer, 2017; Card et al., 2013; Kantenga, 2016; Gaure, 2014; Lentz et al., 2018). Assuming assortative matching is equivalent to assuming that the inventor production function is (weakly) supermodular. Thus, excluding strongly disassortative matching seems an unproblematic assumption made necessary by the fact that I observe production and not wages.

3.3.4 Aggregating Conflicting Rankings

From the above, one can get global rankings of workers (according to their lifetime patent output and productivity). There are also multiple shorter rankings comparing worker productivity within each firm. While they should theoretically all be in agreement, they are not, due to the noise in the data.

Hagedorn et al. (2017) propose to aggregate these rankings by finding the ranking that has the fewest disagreements with the data. Specifically, they count disagreements using the Kendall score, i.e. whenever a candidate ranking ranks

Table 3.1: Firms' Voting Power in Kendall rank aggregation

	Firm X ranking	Firm X yearly patents	Firm Y ranking	Firm Y yearly patents
Inventor A	1	0.3	2	0.3
Inventor B	2	0.2	3	0.2
Inventor C	2	0.2	-	-
Inventor D	3	0.1	1	0.4
Nr. of Ranked Inventors	4		3	
Nr. of Relations	6		3	

Voting power of firms in Kendall rank aggregation. The two firms disagree about the ranking of inventor A and D. However, since firm X has ranked more inventors, the aggregate ranking will reflect its preferences: Currently, the inventors are ranked A, B, C, D, following the preferences of firm X. The issue is whether to put inventor D in first place, following the preferences of firm Y. Yet, moving D to the top generates three disagreements with firm X. Leaving D at the bottom generates only two disagreements with firm Y.

worker x_1 higher than worker x_2, they count how many rankings of individual firms have it the other way around and weight this result with the noise inherent in the observations. Unfortunately, this ranking problem is NP hard, i.e. it cannot be solved exactly with current computers. Hagedorn et al. (2017) show that assuming that the ranking distance function has only one local (and global) minimum yields accurate rankings, even for relatively noisy data.
While this strategy demonstrably yields good approximations of reality when used with typical employer-employee data, this rank aggregation has some properties that are not desirable (Yoo et al., 2019). Specifically, the scheme gives more voting power to complete rankings. To see this, consider table 3.1. The aggregate ranking only reflects the ranking of firm X, even though firm Y ranks inventors exactly the opposite way. This is because firm X has ranked an additional inventor, so it generated quadratically more relations of the form "inventor A is better than inventor B".

Moreno-Centeno and Escobedo (2016) propose to solve this issue by down-weighting each firm's ranking with the number of relations submitted. While this might be a valid response to malicious actors submitting inconsequential rankings to increase their voting power, this is not the problem at hand: Firms presumably have no interest in submitting as many inventor rankings as possible to this data set. With down-weighting, the ranking of the smaller firm would always prevail in any specific disagreement, while the big firms get to rank more inventors. However, I would argue that this is not desirable. Instead, the weight that any firm ranking contributes to ranking A above D should be independent of how many inventors are ranked in between: The productivity of A and B are two cardinal numbers measured with error, and the probability of one being above the other is independent of how many other inventors with productivities between the two are observed.

In the above example, assume that the yearly patents of inventors A, B, C and D are measured without error and that both firms are of equal quality. So, in the Hagedorn et al. (2017) framework, the only explanation for the different rankings is the measurement error in D's productivity: 0.1 and 0.4 are only measurements of the underlying productivity, which, if known, would produce the same ranking of inventors in all firms. If the true productivity is between 0 and 0.2, D should be ranked last. If productivity is above 0.3, D should be ranked first. The fact that firm X has worked with two inventors with productivity 0.2 is not informative about which of these cases is true. This extreme example illustrates the general point that some relationships expressed by the firms are highly correlated according to the underlying model, which a simple Kendall distance approach ignores.

Unfortunately, the correct distance measure according to the underlying model is infeasible: Distance should be measured as the "unlikeliness" of observing the ranking in the data, given that the candidate ranking is true. This requires an involved likelihood computation, which has to be redone for every different proposed ranking. Instead, I propose a simplification in the spirit of Hagedorn et al. (2017): Each inventor contributes the productivity difference necessary to move them to the proposed slot in the ranking, weighted by the precision with which this inventor's probability is measured. In the above example, inventor D would have to have 0.21 less patents per year to be ranked last, as the current ranking suggests. Unlike the Hagedorn et al. (2017) estimator, this distance measure is independent of how many inventors are ranked in between.

Yet, using a new estimator on a new data set in a new context would make any comparison of the results to the previous literature difficult. Hence, I report results for the HLM estimator throughout the paper, in order to stay compatible with the literature.

3.3.5 Ranking Firms within the Model

To rank firms, I will aggregate inventors of similar skill estimates into 100 blocks, following Hagedorn et al. (2017). Within each of these blocks, better firms will produce more with the given inventors. Thus, one can construct 100 firm rankings within each inventor skill level. Aggregating these rankings into one Kendall ranking is less problematic than aggregating rankings within individual firms, because each inventor skill class contains roughly the same number of statements.

Using a theoretical search and matching model for identification also has some limitations: In this model, firms do not take into account that employees are potential channels of knowledge diffusion. Introducing knowledge diffusion into such a model is beyond the current theoretical literature (Hagedorn et al., 2017). This is because such mechanics make match surplus contingent on firms' productivity, the productivity of their competitors, the knowledge each inventor holds and the matching strategies of all other firms and inventors. The effect on matching strategies depends on multiple parameters: on whether individual inventor skill is important to transfer technologies, on whether technology diffusion affects a firm's research quality and on whether the diffusion is permanent after that inventor leaves the firm again. This introduces enough complexity to make the model intractable.

While my model-reliant approach cannot fully cover these mechanics, neither could an approach based on inventor movements (Lamadon et al., 2015; Bonhomme et al., 2017; Lentz et al., 2018) or double fixed effects estimation (Abowd et al., 1999): If inventors move from good to bad firms to not produce but diffuse knowledge, inventors' job ladders do not always lead them to higher quality firms. Likewise, if inventors strategically move between firms, the double fixed effects assumption that worker movements between firms are random is violated. Thus, neither approach in the literature can fully tackle knowledge diffusion through workers, which is problematic in most settings in which these types of estimators are currently used.

However, worker rankings derived from differing patent arrival rates within firms are relatively robust to these concerns. Assume that workers produce patents as described above, but provide additional value depending on how efficient the production of their last employer was. In this case, there is an incentive to poach inventors from high productivity firms, but given that inventors work in the same firm, their patent productivity is still a valid differentiator within. The ranking I use becomes problematic only if patent production at the current firm becomes itself a function of the last firm's productivity. In this sense, my estimator is robust to most simple technology diffusion mechanisms.

Allowing firm quality to change over time also alleviates concerns that peer effects or agglomeration effects might bias the estimation. Moretti (2019) shows that holding both inventor and firm constant, denser agglomeration of matches can increase output by up to 25%. However, this does not have a large impact on the inventor rankings because most good inventors are in highly agglomerated regions: In the US data of Moretti (2019), ten cities account for between 60 and 75% of all patents in the top technology clusters. Thus, most productive inventors are on equal footing in terms of knowledge spillovers. This carries over to PATSTAT, the data basis for this analysis: While detailed geographical information is only available in PATSTAT from 2000 onwards, the available data shows that many patents come from the NUTS2 region with the most patents in each country. Therefore, agglomeration effects do not significantly change the ranking of inventors and will largely be soaked up in the firm quality measure, which captures both the "pure" research skill of the firm and the knowledge spillovers from other nearby firms. The number of firms with significant research departments in more than two NUTS2 regions per country is small.

To account for changes in cluster size and the possibility that firms' innate quality changes over time non-parametrically, I estimate firm quality for every five years separately. I.e., I effectively treat the same firm after five years as a separate firm and rank it again.

3.3.6 Patents and Productivity

To relate the patent data to economic outcomes, I follow the approach of Doraszelski and Jamandreu (2013). They jointly estimate firm level productivity and the effect of endogenously chosen R&D investment on productivity. For

R&D investment, I substitute the observed size of the firm's research department, patenting outcomes and the firm's estimated quality. This has both econometric and theoretical advantages. Doraszelski and Jamandreu (2013) themselves note that it is unclear how much of the time variation of R&D investment is due to accounting practices and how much is economically relevant. Additionally, there is presumably a time lag of unclear length between investment in R&D and actual productivity improvement. Thus, I use the measured quality adjusted size of the research department as an endogenous choice variable. I use realized patenting counts to narrow down when the investments into research paid off.

Specifically, I assume that (log) revenue is a function of (log) inputs and (log) productivity

$$y_{it} = \beta_0 + \beta_k * k_{it} + \beta_m * m_{it} + \beta_l * l_{it} + \omega_{it} \tag{3.4}$$

where k denotes the log of capital in the books, m denotes the log of intermediate inputs and l denotes the log of employees. I also assume that productivity follows a Markov process of the form

$$\omega_{it} = g(\omega_{it-1}; p_{it-1}; \Lambda_{it-1}) + u_{it-1} \tag{3.5}$$

where p_{it-1} denotes the number of patents a firm has filed in the last year, Λ_{it-1} denotes the quality weighted size of the firm's research department and ω_{it-1} is lagged productivity. As is common in the productivity estimation literature, I will approximate the function $g(.)$ by a third order polynomial of all its terms. Including both the researchers of the firm and their output allows for a positive effect of this highly skilled personnel even before they produce patentable research.

The equations are identified by the timing assumptions prevalent in this literature: It is assumed that the firm has to decide on investment and thus k at the end of the previous year, before knowing its productivity. Thus, capital is by assumption uncorrelated with ω_{it} in equation (3.4). In contrast, l and m are optimally chosen, given the productivity the firm expects. The law of motion yields that productivity is predicted by ω_{it-1},p_{it-1} and Λ_{it-1}. Thus, l and m are exogenous when controlling for the productivity the firm could expect. Thus, I estimate

$$\omega_{it} = \beta_0 + \beta_k * k_{it} + \beta_m * m_{it} + \beta_l * l_{it} + g(\omega_{it-1}; p_{it-1}; \Lambda_{it-1}) + u_{it-1} \tag{3.6}$$

which yields unbiased estimates of $\beta_k, \beta_l \& \beta_m$. For a detailed and general discussion of this control function approach to production function estimation, see De Loecker et al. (2016). Since I cannot control for prices with the data at hand, I follow Loecker and Warzynski (2012) to compute the markups implied by firm behavior: In static equilibrium, firms will equate revenue productivity of a flexible factor with this factor's costs. This can be used to back out the markup implied by that firm's input choice.

3.4 Results and Stylized Facts

This section presents the results from the above estimation and distills it into stylized facts. I explore staples of employer-employee matching estimation (assortative matching, patent invention), but also the concentration of technological capabilities in firms. Ultimately, the empirical analysis alone cannot decide on the welfare implications of the observed changes. A model or additional information is needed to differentiate between welfare enhancing and decreasing developments.

3.4.1 Matching of Inventors and Firms

Firms and inventors generally match assortatively, i.e. good inventors move to good firms. To present the results from all patenting authorities and technology clusters succinctly, figure 3.9 pools technology clusters and time periods and shows how often the respective combination of firm and inventor quality is observed.

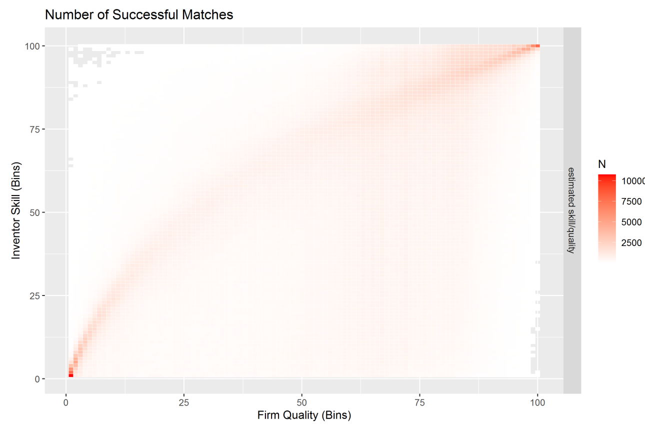

Figure 3.9: This graph shows the matching of inventors to firms, pooling all time periods (1974-2012) and technology clusters. Red areas are densely populated with spells, while blue areas are largely empty. Matching is assortative, i.e. better inventors go to better firms. Grey areas of the plane have fewer than 50 matches.

Evidently, in general, highly skilled inventors seek out high quality firms. Inventors seem to be less picky than firms, so the matching area is curved upwards: An inventor in the 50% skill percentile will only match with firms in the 25% percentile of quality. In general, the core matching area is quite narrow, with the rest of all matches dispersed relatively evenly across the plane.

Figure 3.9 does not take into account the different lengths of employment spells. However, there is no strong pattern regarding the duration of matches: Matches within every cell of the plane are estimated to last between 7 and 10 years on average. Hence, the number of expended hours in every cell largely follows the number of matches.

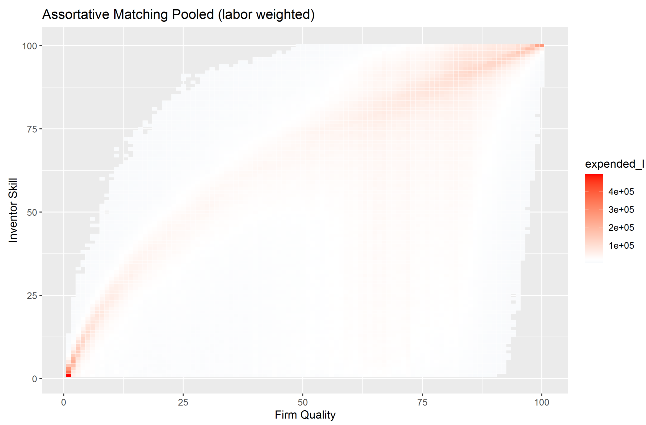

Figure 3.10: This graph shows the labor input provided by matches of inventors of a certain skill and firms of a certain quality, pooling all time periods and communities. Matching is assortative, i.e. better inventors go to better firms.

Assortative matching not only differs between technology clusters, but also evolves over time. Thus, the correlation of inventor skill and firm quality changes over time. The correlation captures linear relationships, yet the pattern in figure 3.9 is still close enough to linear to be captured this way. Figure 3.11 documents the development of the correlation over time for the five biggest technology clusters and the three largest patenting authorities.

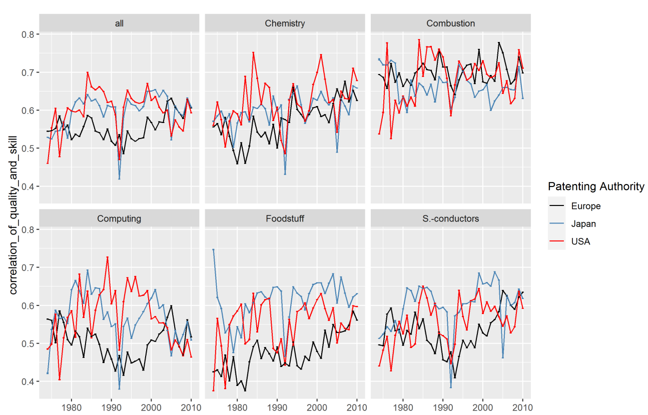

Figure 3.11: Evolution of the correlation between inventor skill and firm quality within matches for the biggest technology clusters in the largest patenting authorities. Assortative matching increases in most technology clusters and over all.

The correlation is increasing over time and in most communities. The overall increase from 1974 to 2010 in the US is from 0.45 to 0.6, or 33% (top panel). This amounts to about 0.004 per year. The rise is not monotone: Assortative matching peaked between 1985 and 2000 at around 0.65. It has been decreasing slightly from since then.

The outlier with respect to the overall trend towards assortative matching is computing: After 1985, assortative matching is continuously sliding downwards. Combustion maintains its high level of assortative matching, while chemistry, foodstuffs and semiconducturs are rising.

More mature technologies in concentrated industries seem to experience rising assortative matching. Semiconductors is a prime example of a technology focused solely on a specific technological problem: increasing the number of transistors in integrated circuits. Bloom et al. (2017) cite semiconductors as one of their prime examples for decreasing technology growth, as it becomes harder and harder to double transistor numbers.

To determine whether patenting rates decline in semiconductors and the economy overall, one has to turn to the patent invention function λ. Overall productivity will be determined by how many inventor years are invested in each cell and how the productivity of these cells changes over time.

3.4.2 Patent Invention Function

The estimated patent invention functions are highly stable over time and put more weight on inventor rather than firm quality. I estimate the patent invention function non-parametrically on the same grid as assortative matching: I group workers and firms into 100 percentiles according to their ranking and estimate the labor input weighted average within each combination.

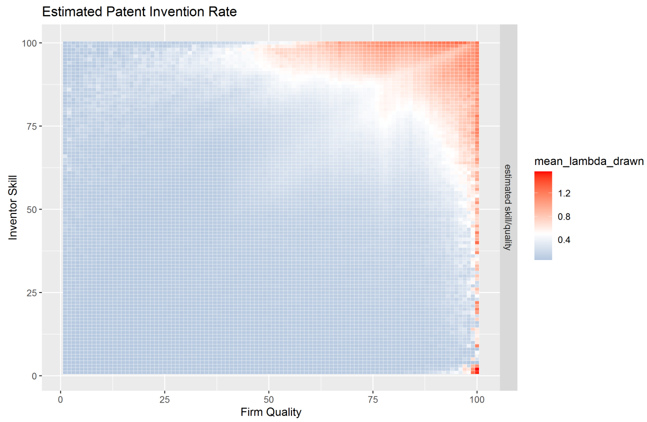

Figure 3.12: Pooled Patent Invention Function: Expected number of patent author shares as a function of firm quality and inventor skill. Matches of highly skilled inventors with high quality firms have much higher patent arrival rates. Inventor skill is more important than firm quality.

Inventor skill and firm quality are both important drivers of patent inventions, however, inventor skill is slightly more important: E.g. an inventor in the top 1% matched with a firm in the middle of the distribution will create more than one patent per year, while the reverse combination is less productive.

A large debate in the literature is whether inventions have become harder to find, i.e. whether the rate of patenting λ has slowed down. More inventions can conceptually be the result of more efficient matching of inventors and firms, of matches of a given quality becoming more productive, or of more inventors.

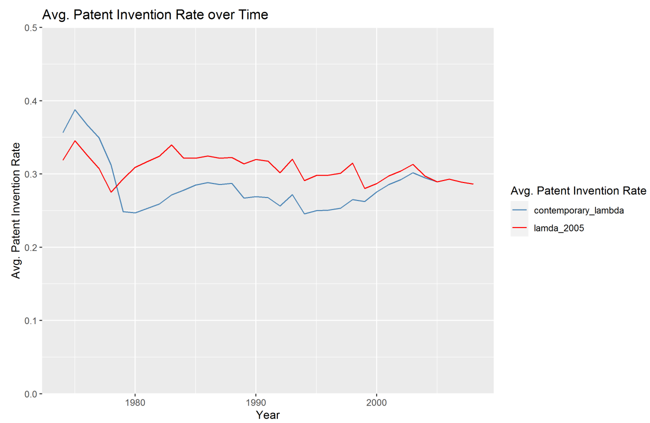

Figure 3.13: Average productivity of matches over time. The blue line gives the average estimated productivity of all matches formed in any one year. The blue line gives the same, but using the patent invention function of 2005-2010 for the whole data set. If matches could have used the patent invention function of 2005-2010, they would have produced more patents than they did. The only exception is at the very beginning of the data set (1975-1908), which is also the production function estimated with the lowest precision due to relatively few observations in many cells.

In general, the patent invention rate changes very little. However, if there is a trend at all, patents were slightly easier to produce with the patent invention function of 2005-2010 than they were before (figure 3.13). The patent invention rate of matches started between 1974-1979 is the highest overall, but it is the least precisely estimated rate, due to few matches in many of the bin combinations.

3.4.3 Concentration of Technological Competences

Patenting is a highly concentrated activity, even among those few firms who patent at all (Figure 3.1). Within patenting authorities and technology clusters, patents are still highly concentrated among the top 5% of firms (figure 3.14). Patenting at all major patenting authorities is also becoming more concentrated over time (figure 3.15). Patenting by small firms is declining the fastest.

Figure 3.16 shows that large technology clusters (with many patents) are more concentrated than smaller ones. Technology clusters where more inventions are patented each year have a higher share of innovative contributions by the top 5% of firms. The fitted relationship is positive even though the largest and most

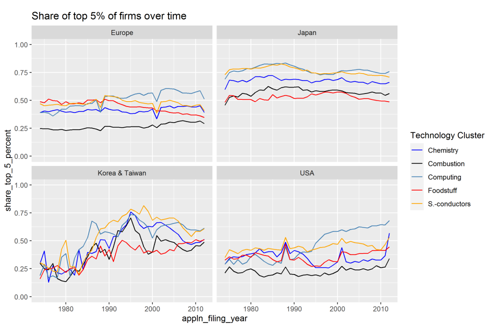

Figure 3.14: Concentration in the largest technology clusters over time. Concentration is measured as the share of inventions made by inventors working with the top 5% of firms (by patent output). If two inventors from different firms are listed under the same invention, both firms receive half an invention.

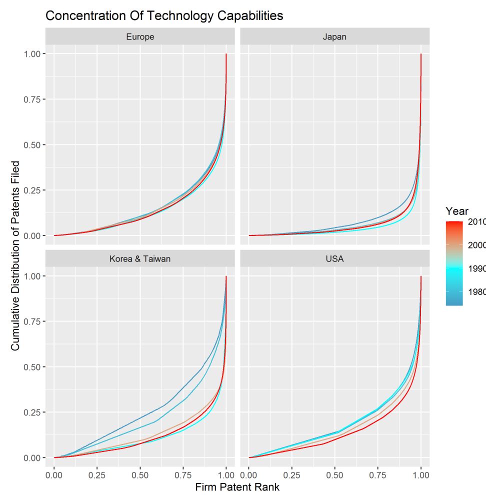

Figure 3.15: Cumulative distribution of patents per firm. Every firm is assigned its share of patents in each technology cluster and time. Concentration is continuously rising in the US and Korea & Taiwan, rising slowly in Europe and rising and then slightly falling in Japan.

concentrated technology clusters are beyond the right edge of the graph. Because concentrated fields are larger, the overall concentration is even higher than the average concentration within fields or IPC classes.

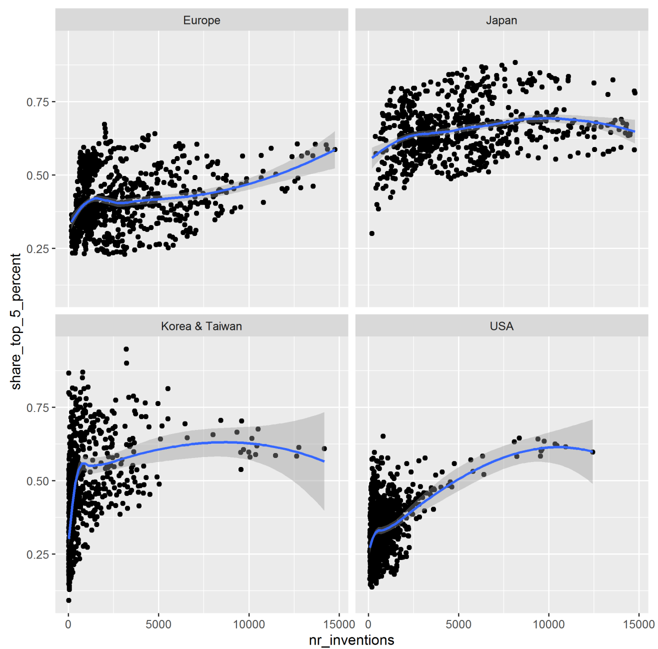

Figure 3.16: Concentration as a function of the number of inventions within a sector. Each observation marks a different technology cluster at one point in time. The x axis denotes how many patents were filed in one year, the y axis gives the share of the top 5% of firms. There is a positive correlation between the two: The bigger the technology cluster, the larger is the share of patenting done by the top 5% of firms.

All in all, innovation has been highly concentrated among few firms throughout the time period. Active technology clusters are also the more concentrated ones. Outside the absolute top, well established firms (with more than 50 patents every year) produce a large share of all patents. These firms are a tiny minority of all firms in the economy. The ability to regularly produce more than 50 patents represents a sizable investment from the firm, one that most other firms seem unable to make. Additionally, good inventors are overwhelmingly concentrated in large established firms, a trend that has increased over the time covered. Chapter 4 will explore potential causal forces behind this correlation.

3.4.4 Knowledge Production and Profits

I find that patenting increases profits faster than productivity. This is troubling in itself, since patents are granted to incentivize firms to produce public goods, not help them appropriate private profits. The results hold in a simple setting with an exogenous production function and when using a combination of the Doraszelski and Jamandreu (2013) and the Loecker and Warzynski (2012) estimator to jointly estimate markups and the law of motion of productivity.

Table 3.2: Knowledge Production and Profits

	(1) $ln(EBIT)$	(2) $ln(\omega_{simple})$	(3) $ln(\omega)$	(4) μ	(5) $ln(EBIT)$
log(number of patents)	0.0536***	0.0046	0.0030	-0.0284	0.0566
	(0.0081)	(0.0042)	(0.0026)	(0.1269)	(0.0327)
Inflow Movers	-	-	0.0048*	-0.0007	0.1986***
			(0.0036)	(0.0602)	(0.0454)
Rank Firm	-	-	-0.0004	0.0024	-0.0031
			(0.0002)	(0.0046)	(0.0023)
Control Function	NO	NO	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES
Observations	27332	27332	14771	14771	14771

$ln(\omega_{simple})$, ω & $ln(EBIT)$ denote log productivity with a $\frac{2}{3};\frac{1}{3}$ production function, log productivity with an estimated production function and profits. μ denotes firms' markups. Production function as in De Loecker & Warzynski 2012; effect of patents as in Doraszelski & Jaumandreu 2013. Bootstrapped Standard Errors (n=500) in parentheses.

Table 3.2 reports the results of my estimation. Columns 1 and 2 report simple FE estimates, to alleviate concerns about the validity of production function estimation. According to these results, a firm can expect to increase profits by about 5% when they double their patenting output.

Columns 3 - 5 report the results from a joint semiparametric estimation of the production function and the law of motion of productivity. In the semiparametric estimation, I include the inflow of inventors moving to firms and the rank of the firm in the research quality rating as potential variables into the law of motion. This tests the hypotheses that moving inventors bring technological knowledge with them or that a firm's research quality proxies for its absorptive capacities. Given the patents a firm is already applying for, research quality does not offer additional benefits. The number of inventors that move to the firm does however increase both productivity and profits. This further supports the hypothesis that moving inventors diffuse technology.

3.4.5 Inventor Mobility and Technology Diffusion

I find that between 2000 and 2010, inventors who are leaving top firms increasingly move to other top firms, instead of transferring their knowledge to less productive firms. Since technology personnel movement is an important driver of technology diffusion, this might explain the increasing gap between "The Best and the Rest" in a large number of countries (Andrews et al., 2016; Gal, 2017). This dispersion might also hurt overall productivity growth (Akcigit and Ates, 2019). Firms themselves rank retaining knowledgeable employees as one of their most important strategies for protecting intellectual property (Harhoff, 1997). To measure technology diffusion through moving inventors, I turn to the sample of patent data matched with firm productivity estimates and rank all firms within a region and five year time period. Splitting the resulting ranking into 50 productivity classes, I count movements of inventors from the top 10% of firms to the rest. I analyze the top 10% of firms to synchronize with the productivity dispersion literature, which considers the top 10% of firms "frontier firms" worthy of special attention. The matched sample between PATSTAT and AMADEUS is only large enough between 2000 and 2010. During this time frame, the trend of moving only between top firms is stable and persistent.

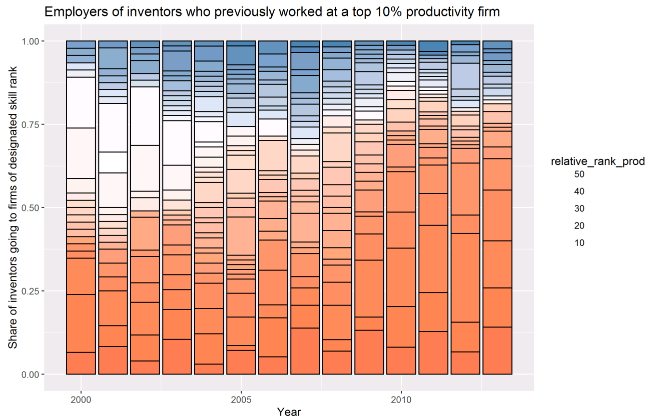

Figure 3.17: The graph shows the subsequent employers of inventors who have left a firm in the top 10% productivity decile. Firms are ranked according to their productivity and grouped into 50 different skill classes, 50 designating the most productive 2% of firms.

Figure 3.17 shows which firms inventors move to after having worked for a top firm. Movements from top firms to laggard firms are becoming less frequent over time. This decline is not simply driven by overall rising concentration, as the output share of the top firms has only increased moderately. Instead, the matching behavior of productive and unproductive firms is driving this change. Documenting inventor rankings between firms is in the spirit of a branch of endogenous growth models focused on technology diffusion (Arkolakis et al., 2018). These models focus less on firms' R&D decisions and more on the random meetings of inventor-entrepreneurs and the resulting exchange of ideas. In these models, equilibrium productivity growth is determined both by how many new ideas are created and how fast these diffuse. While fast diffusion leads to faster growth, it also diminishes the incentives to invent new technologies, since the associated technological edge is lost quickly.

3.4.6 Summary of Empirical Findings

A major result of the paper is that inventors and firms have matched assortatively since 1974 and that this has increased over time. With the only notable exception of computing, most technology clusters exhibit this trend. Throughout the time period, the higher quality firms increased their quality weighted share

of researchers.
The estimated patent invention functions are largely stable over time and put more weight on inventor rather than firm quality. Because the contributions of firms to patenting probability are not large, rematching inventors and firms can only lead to small increases in production. In this, the paper comes to a similar conclusion as Hagedorn et al. (2017), although the method has been altered substantially and the context is different.
The stability of the patent invention function seems to contradict popular explanations of technology stagnation: It does not seem like inventions are getting harder to find. However, the arrival rate of patent families is also influenced by which projects firms decide to undertake in the first place: There is strong evidence that firms attempt more incremental and applied research projects (Arora et al., 2019), while patents with more scientific content are more valuable (Poege et al., 2019). If firms are racing each other to the same ideas more often, firms start smaller projects in equilibrium (Silipo, 2005).

3.5 Conclusion

I analyze the matching of firms and inventors and the productivity of the resulting matches as a potential driver of slowing technology growth. I document which matches are formed and how much each party contributes to patent invention. To answer these questions, I transfer empirical strategies used in the search and matching labor market literature to the PATSTAT patent data from 1974-2010, which I use as an employer-employee data set.

Assortative matching has risen over time in nearly all technology clusters. Highly skilled inventors increasingly match with firms with a high research quality. High quality firms produce more patents and are larger on average. Decreasing movement of inventors might cause a decrease in knowledge diffusion documented by Akcigit and Ates (2019); Andrews et al. (2016); Gal (2017). I merge conventional firm production productivity estimates to my data and find that less and less inventors move from top productivity firms to firms with lower productivity. I find that such movements are – when they still happen – associated with productivity and size increases for the receiving firm. The same pattern holds true for newly invented patents between 2000 and 2010 (there is no matched data for earlier years).

It is often hypothesized that ideas are getting harder to find. This would mean that matches between inventors and firms of a given quality produce less patents today than they did previously. Yet, matches' estimated productivity is not declining: If matches from the 80s or 90s had used the patent invention function of 2005-2010, they would have produced slightly more patents, not less.

These results open up interesting avenues for future research: First, narrowing the scope of my analysis to a specific country with high quality firm data would allow to assign specific product lines to specific technologies and measure markups with a higher degree of certainty. More complete data could be used to more precisely measure the contribution of assortative matching to productivity dispersion, markups and profits using state of the art markup estimators. I committed to a global scope for this paper to understand patenting behaviour across the developed world, since most contributions on the technology growth slowdown also assume that it is a global phenomenon. However, diving deeper into specific countries with a higher quality data set could enhance our understanding of firm level responses.

Second, the welfare implications of the trends documented also hinge on the type of innovation that patents represent. To better understand these welfare results, chapter 4 develops an endogenous growth model containing an inventor-firm matching labor market. Firms hire highly skilled inventors for two reasons: either to pursue more difficult, disruptive inventions or to prevent these inventors from being disruptive. Firms fear disruptive inventions because disruption changes the technology underlying their product and makes firms' traditional inventors obsolete. In this model, assortative matching can be beneficial if it means that highly skilled inventors go to firms engaged in difficult, disruptive research. Assortative matching can be detrimental if it means that good, large firms poach their competition. Despite declining growth, this is rational behavior from the viewpoint of the firms: The correlation between patents and profits is substantial in the model and in the data.

Chapter 4

An Endogenous Growth Model with an Inventor Labor Market

4.1 Introduction

Expanding on the empirical analysis in chapter 3, I develop an endogenous growth model in which growth slows down because successful firms inhibit disruptive innovation. This model can reconcile a set of seemingly contradictory findings: TFP growth and scientific output per researcher seem to decline, while firms hire an increasing number of researchers for non-decreasing wages (Cowen and Southwood, 2019; Bloom et al., 2017). Likewise, the scientific content of patents is declining (Arora et al., 2019), despite patents with more scientific content being more valuable (Poege et al., 2019). The model explains these trends as outcomes of firms' optimal research strategies: Large firms' profits depend on the fate of their specialty technology. Thus, they cling to incremental innovation and undertake defensive measures to prevent disruption.

The actions of two types of firms drive the fate of the model economy: First, there are disruptive firms. Disruptors do not sell any products, but try to invent a fundamentally different technology. Bill Gates and Paul Allen working in a garage to revolutionize home computing were an archetypical disruptive firm. If disruptive inventors are successful, they create a new producing firm with better production technology than that of any currently existing producer. Producing firms, the second firm type, actually earn revenue in the consumer market by selling a product. Producers take an underlying technology invented by disruptive firms and develop it into a product. Producing firms improve their technology incrementally in order to produce a product of higher quality. Steady technological progress requires a mixture of both types of inventions: Disruptive inventions alone never create a consumer product, only ever more advanced production technologies. Incremental inventions alone lead to a slowing rate of technology growth: As incremental inventors strain against the limits of the underlying production technology, the rate of technology growth within each technology declines over time. Every disruptive invention allows incremental inventors to work with a more advanced basic technology and thus increases the value of future incremental improvements by the factor ω. This tension between disruption and incremental growth is the central tradeoff in the model and how well the market economy handles it determines economic growth.

Neither disruptive nor producing firms can conduct research on their own: Firms need inventors to make inventions for them. Firms of both types hire incremental or disruptive inventors on a search and matching labor market. Disruptive and incremental inventors enter the economy and match with firms at fixed rates. The value of each firm is partly determined by the stock of inventors it has hired and those it can hire in the future. Incremental inventors are specialized in their current technology and cannot contribute to other technologies. Thus, whenever a firm switches the technology underlying its products, it effectively loses all incremental inventors it has hired so far. Inserting this labor market into an endogenous growth model is the primary new assumption compared to the literature. This new assumption drives the new findings: Firms try to protect their assets (incremental inventors) from being made obsolete by disruptive innovation.

Successful producing firms can slow down technology disruption by hiring the inventors that disruptive firms would need to innovate. Thus, some firms in the economy actively resist technology growth. Technological progress depends not only on investment in R&D, but also on overcoming this resistance. This is the main mechanism that follows from the introduced assumptions and sets this paper apart from the rest of the endogenous growth literature, which views innovation as the result of investment only.

The model can recreate the empirical trends documented in chapter 3:

- Patent invention rates are a function of both inventor skill and firm research quality.
- Highly skilled inventors strongly sort to high quality research firms (correlation 0.5-0.8).
- Assortative matching increases within technology clusters.
- Patents are highly concentrated within technology clusters.
- Aggregate productivity growth decelerates.

The model can reproduce an economy with similar developments: If producing firms with a high research quality successfully poach all highly skilled inventors, assortative matching is high. The bulk of inventions will be small and incremental with a low productivity effect. However, the model also supports another equilibrium with high assortative matching. In this second equilibrium, high quality inventors work at disruptive firms and frequent disruptive inventions keep producers small and technology growth high. This equilibrium does not fit the observed trends.

A fictitious social planner has to chose between these two equilibria. Which of the two he would pick crucially depends on the weight that the social planner puts on future generations: A disruptive invention will increase economic growth long-term, but the benefits will accrue to future inventors and future firms. In contrast, the current incremental inventors and producing firms unambiguously lose after a disruptive invention. If the current agents die before the growth increase from a disruptive innovation creates value, the social planner cannot compensate them and the low-growth equilibrium with incremental innovations is Pareto-optimal, even though it does not maximize GDP. If people in the model live long enough, the social planner could use the additional GDP to compensate the losers from a disruptive innovation.

A large literature is concerned with the growing dispersion of firm level productivity (Gal et al., 2016) and declining aggregate productivity growth (Gordon,

2016) throughout the developed world. The literature discusses several different explanations for these phenomena:

Akcigit and Ates (2019) argue that slowing technology diffusion is itself the most likely source of slowing technology growth. Lucking et al. (2019) argue that technology diffusion is still about as fast as it was in the 1980s. However, they do find that technology diffusion was faster during the growth acceleration associated with IT in the 1990s. In my model, growth is driven by disruptive innovation, while incremental inventions (and their diffusion) influence the level of economic activity. However, the model I present also features an inventor-firm labor market, which can serve as micro-foundation for technology diffusion in the endogenous growth model.

Another school of thought argues that ideas are getting harder to find and technology growth thus slows down endogenously. Gordon (2016) makes this point. Bloom et al. (2017) showed that more and more researchers are necessary to double e.g. computing power or crop yields per acre. My paper takes this finding seriously, but offers an alternative interpretation: The very fact that firms invest so many resources in solving the same problems using the same technologies indicates that they are engaged in incremental innovation. Thus, the findings of Bloom et al. (2017) are troublesome because they show a misallocation of inventive talent to incremental innovation with declining returns. Yet, this does not necessarily mean that disruptive ideas are becoming harder to find.

My model is built on the framework of Akcigit and Kerr (2018), who assume that firms are proficient in specific technology clusters. I understand technology clusters as more than just one new product, they denote distinct technologies behind multiple individual products, like "telegraphy" or "internal combustion engine". Incremental inventions within these clusters generate higher quality products. In departure from Akcigit and Kerr (2018), firms cannot invent on their own and have to hire inventors specialized in a technology cluster on a search and matching labor market. The labor market for inventors in each cluster corresponds to the results presented in the empirical chapter in section 3.4. Specifically, I develop how innovation affects firms' technology $\frac{\partial q}{\partial p}$ and how firms' technology determines profits $\frac{\partial \pi^*}{\partial q}$. Together, these factors determine the value of an invention $V(p)$ in equation (3.3).

My paper also speaks to a larger theoretical literature on market failures that misdirect innovation. Firms under-invest in research that unlocks follow-up inventions, because they cannot profit from the inventions other firms will make, as in Hopenhayn et al. (2006); Denicolò (2000); Scotchmer (1991). In general, firms can only appropriate a share of the overall welfare increases that result from their inventions. Since this share is not constant across inventions, firms over-invest in inventions where they can appropriate a high share of the returns (Bryan and Lemus, 2017). In the model presented here, producing firms can only appropriate the returns from incremental innovation, which drives aggregate behavior.

In a larger context, the paper relates to literature on the efficacy of the current system to reward innovative firms. The theoretical and experimental literature suggests that patents are not able to optimally steer the direction of innovation in general: If only a finite number of research direction is available, firms race each other to the most lucrative patents and incur wasteful parallel investment (Zizzo, 2002; Silipo, 2005; Breitmoser et al., 2010). Both in the US (Jaffe, 2000) and Japan (Sakakibara and Branstetter, 2001), firms do not react conclusively to substantial changes in patenting protection. Nevertheless, in my model, the market failure can be corrected by policy interventions. Since technology monopolists are misdirecting innovation, policy should break up existing monopolies and prevent mergers and buy-outs of start-ups. Likewise, any policy that increases the transferability of inventor skills makes technology markets larger and thus harder to monopolize.

Beyond the theoretical literature, there is substantial empirical support for the monopolization of research fields, which is conceptually adjacent to the proposed model: Thompson and Kuhn (2017) use patent races between firms to compare the first and second research team and thus patent holders and followers. They find that patents preclude competitors from follow-up innovation and make the winner of patent races more dominant in the associated technology field. In the semiconductor industry, increased patent protection seems to have led to defensive patenting instead of innovation (Hall and Ziedonis, 2001). Across industries, the correlation between patent protection and innovation is negative, which Bessen and Maskin (2009) explain by the negative effect of patents on sequential inventions. This study extends the principal insights of this literature to a context of inventor-firm labor market matching in an endogenous growth model.

This paper also links into the literature around the documented rise of firm profits and markups (Barkai, 2017; De Loecker and Eeckhout, 2017). The model predicts that firms with high market power engage in qualitatively different R&D. Only small, competitive firms invest in disruptive technology to – if successful – themselves become large firms linked to a technology. After that, their research portfolio will become much more incremental. These predictions could be tested with firm level patent data.

The remainder of the paper is structured as follows: Section 4.2 lays out the assumptions and mechanisms of the model. The section also discusses various possibilities for extensions of the model and their implications. Section 4.3 discusses the policy implications of the model and the strategy of a social planner. Section 4.4 concludes the analysis.

4.2 Model

4.2.1 Research

The inventors who drive technological progress are at the heart of this endogenous growth model. Inventors choose the firm they work with and the type of innovation they pursue. Producing firms poach inventors from disruptive firms to protect their technologies from disruption.

Technology is differentiated into broad fields or disciplines like "telecommunications" or "electricity generation". Within each of these fields, technology clusters (following the terminology of Akcigit and Kerr, 2018) denote distinct areas of knowledge like the clusters "telegraphy" or "satellite communications" in the field "telecommunications". These clusters are areas of expertise for individual inventors, who cannot be experts in whole fields or even all sciences.

Firms cannot conduct research on their own and have to hire inventors. The majority of inventors are specialists who studied one specific technology cluster and are dedicated to improving it further. Every invention these incremental inventors make increases the product quality of their firm, but does not change the general technology structure. An example of incremental inventors are the engineers who improve the internal combustion engine. Incremental inventors cannot contribute to the economy if this technology becomes obsolete. Because of this restriction, technology clusters play a large role in inventors' and firms' calculations. Throughout the rest of the paper, I will use the words cluster and technology cluster interchangeably.

Occasionally, major breakthroughs in a technology field create an entirely new, better technology cluster within the same field. An example are current efforts to use gas, hydrogen or electric energy to power cars. If successful, electric cars would then form another technology cluster within the broader field of "vehicle construction". Disruptive inventions are proofs of concepts for better technologies: The first telegraph, the first power line or the first electrical train were not viable consumer products, but demonstrated the feasibility of the technology. Subsequent incremental innovations then create actual products that can enter the market. Each cluster is better than the last one in the sense that it enables more impactful incremental follow-up innovation.

Within each technology field, there exists a group of disruptive firms who aim to create such breakthroughs. These firms do not sell any products, but employ disruptive inventors to generate prototypes of future production technologies. Whenever these firms are successful, a new technology cluster is born and the old cluster becomes obsolete. Old incremental inventors can no longer contribute to products based on the new technology, but disruptive inventors and firms can immediately work on disrupting the new technology again. The disrupting firm also founds a new producing firm which will use the newly created technology.

Clusters are indexed by their field and a running number c. Taking the field of telecommunication as an example, the telegraph might be $c = 1$, the telephone might be $c = 2$ and so forth. Slightly abusing notation, I will drop the index $field$ for now, since all fields in the model are symmetrical and follow the same logic. Thus, the index is only relevant when aggregating over the whole economy. In the following, capitalized variables denote aggregate variables (like the probability for disruption in a technology field Λ^{dis}) and lower case letters describe microeconomic variables (like the number of patents for firm p $nr_p^{patents}$). Parameter notations follow precedents in the literature whenever possible.

The only point of disruptive inventions is to enable incremental follow-up improvements. The quality that these incremental inventions generate rises the higher the cluster. The quality improvement from one incremental invention is

$$\Delta q(c) = \omega^c \tag{4.1}$$

where c denotes the number of the cluster. In the above example, an incremental invention that improves the telegraph would generate ω^1 additional quality for the inventing firm. An incremental improvement of the telephone would create ω^2. Thus, parameter $\omega > 1$ determines how substantial the gains from disruptive inventions are: If $\omega = 1.20$, a telephone improvement would generate 20% more quality than a telegraph refinement.

4.2.2 Poaching Disruptive Inventors

There are two different types of inventors, who pursue different types of inventions: First, there are incremental inventors who make improvements to the existing technology of their employers. Second, there are disruptive inventors, who generate the next technology cluster and found a producing firm with the new technology.

The central conflict of the model is between producing and disruptive firms: Producing firms fear technology disruptions and can poach disruptive inventors to prevent disruption. While this behavior slows down technology growth, it also protects the assets of producing firms: The value of an incremental firm comes from its patents, its current stock of inventors and the value of its future hires

$$V_p = nr_p^{patents} * V^{patent} + V_p^{inventors}(V^{patent}, \lambda_p^{inv}, r, \delta, \Lambda^{dis}) + V_p^{hires}(V^{patent}, \lambda_p^{inv}, r, \delta, \Lambda^{dis})$$

The first term denotes the stream of future profits that producing firm p can derive from its incremental patents ($nr_p^{patents}$). The assumptions about consumer demand ensure that every patent has the same constant value V^{patent}. Alternatively, one could also assume that patents are tradeable without costs, which means that each patent must have the same value in equilibrium, no matter which firm invented it. Patents do not expire and the product improvements they allow carry over to the next technology cluster (as in Akcigit and Kerr, 2018), which keeps the optimization problem of the producers simple. This assumption works against the mechanism I propose in this paper: If patents were also invalidated by disruption, producing firms would have even more reason to fear and prevent it.

The second term describes the value of the inventors that the firm currently employs. It is a function of the value of a single patent V^{patent} and the rate at which the inventors of producing firm p create patents λ_p^{inv}. This stream of future patents is discounted with the interest rate r, the rate at which inventors leave the economy δ and the rate at which disruptive inventions occur Λ^{dis}, since disruptive inventions will make the stock of incremental inventors obsolete. The specific functional form of the discount factor is determined by the equilibrium evolution of Λ^{dis}.

The third term denotes the value a firm derives from the inventors it will hire in the future. New producing firms can enter the economy at any point by paying the entry fee f_e and draw a research quality y_p. Hence, the ex ante expected value of hiring inventors in the future has to be f_e. The ex post value might be different, because firms know which research quality they have drawn and high quality firms might profit more from hiring inventors. In this case, high quality firms would have an additional incentive to prevent disruption. I take the conservative approach and assume that hiring costs increase in quality, too. This reduces the incentive for high quality firms to poach disruptive inventors and thus works against the central mechanism of the model. It also simplifies the following calculations.

The rate of disruptive innovation affects the value of producing firm p through the value of its inventor stock: Disruptive inventions do not affect the value of patents (which do not become obsolete whenever a disruptive invention hits) and they do not affect the value of inventors hired in the future (because even if the value of future hires goes up, new firms will enter the market to take advantage, reducing the stream of inventors that go to any one firm).

To protect their valuable stock of inventors, producing firms interfere in the labor market for disruptive inventors. Each disruptive inventor that a producing firm can secure will decrease the likelihood of disruption. Whenever one of the poached disruptive inventors of firm p would have made a disruptive invention, the firm has effectively saved its entire stock of incremental inventors. The motive for poaching disruptive inventors thus is stronger the larger the producing firm is. To be able to poach, the value of preventing disruptive inventions for the producing firm must be higher than the value of the disruptive inventions themselves.

$$V_p^{Dis} = \lambda_i^{dis} \frac{\partial V_p^{inventors}(V^{patent}, \lambda_p^{inv}, r, \delta, \Lambda^{dis})}{\partial \Lambda^{dis}} * f(\lambda_p^{inv}, \eta) \geq \lambda_i^{dis} * V_i^{dis} \qquad (4.2)$$

The value of hindering disruptive inventions is a product of three terms. The first term is the rate at which the inventor would have caused disruptions (λ_i^{dis}). However, since more productive inventors would also create more inventions, λ_i^{dis} appears on both sides of the equation and does not affect the calculation of whether or not to hire any specific inventor.

The second term denotes the amount by which the firms' incremental inventors increase in value if Λ^{Dis} falls: A lower probability of disruption does not increase the number of patents that incremental inventors produce, but it increases the expected time during which they can produce. This increases the value of each inventor.

The third term $f(.)$ captures the size of the firms' research department measured by the firms' patent arrival rate λ_p^{inv} and the possibility that it will grow in the

future due to the rate of new hires η.
A poached disruptive inventor not only directly reduces the rate of disruptive inventions today, but also has some option value: First, the rate of disruptive inventions in the future might change, which would change how valuable the inventor is. Second, firms might hire more incremental inventors and thus he would be able to protect more assets from disruption. The functional form of $f(.)$ and even the proposition that V_p^{Dis} can neatly be separated into a product of the three terms depend on the evolution of Λ^{dis} and the size of a firm's research department over time.

This value of shutting down a disruptive inventor is related to the problem of the social planner: The destruction of all incremental inventors is a social cost of any disruptive invention. However, the social planner weighs it quite differently: The social planner does

- not take into account the quality of any specific firm $f(y)$: The social planner will take into account the value of all obsolete inventors and thus calculate with the average firm quality. Yet, even if this value is low, the highest quality firms might already have incentives to hinder disruption.

- not take into account the loss of the stream of future inventors η. These inventors are not lost to the economy, only to the no longer existing obsolete firms.

- instead take into account the fact that future inventors are able to start in a better technology cluster as a positive of disruption. However, already existing firms are wedded to already existing technologies and cannot profit from the future higher rate of technological progress.

To find the specific functional form of equation (4.2) and determine which firms will poach how many disruptive inventors, I will now discuss the inventor labor markets for incremental and disruptive inventors.

4.2.3 Labor Markets for Incremental Inventors

I model inventor labor markets as slightly simplified versions of standard search and matching labor markets. Standard versions are not tractable outside of the steady state. Yet, it is a central feature of the model that disruptive inventions upset the steady state and thus it is imperative that the value of inventors and the equilibrium strategies remain manageable on the path towards a new steady state. Thus, I make a few simplifying assumptions. I demonstrate that the qualitative results do not hinge on these assumptions whenever I introduce them.

The labor markets for incremental inventors bring together producing firms who want to improve the quality of their product with fresh graduates from university within each technology field.

New producing firms can be founded at any time in any frontier technology cluster by paying the entry fee $f_e\omega^c$. Firms draw a research quality y_p from a uniform distribution. These firms then participate in the labor market for incremental inventors for that cluster. The expected value of the stream of future inventors net of the cost of vacancies will thus always equal $f_e\omega^c$, or additional firms will enter.

Prospective incremental inventors leave university and enter the labor market for each technology field at rate η. These graduates draw an ability x_i and then choose a technology cluster to specialize in. It is clearly optimal to choose the most advanced technology cluster within each field: Even if there was a market for improving obsolete technology, patents in more advanced clusters enable larger productivity gains, boosting profits and wages.

Since graduates have to fit the research projects firms hire them for, they cannot just start at any firm. Instead, graduates search for firms' open vacancies. In the standard search and matching labor market, η graduates enter the economy at any point in time and become unemployed inventors. This builds up a mass of unemployed inventors which slowly matches with firms or exits the market again. If the economy is in steady state, the masses of graduating, unemployed and employed inventors are constant. However, if the cluster was only just created through a disruptive invention, this creates a complicated path to the steady state (see e.g. Rogerson et al. (2005) or Hagedorn et al. (2017) for an overview over popular modeling approaches).

To simplify the equilibrium path outside of the eventual steady state, I assume that graduates enter the labor market and immediately find a match among the available vacancies. Unmatched inventors have to leave the economy because they lose their connection to recent developments. The research avenues that are represented by vacancies also become superseded by new approaches if they do not match. This reduces the complexity of the labor market, because the mass of unemployed inventors does not matter for the equilibrium anymore, since they cannot contribute to the economy. This leads to the same steady state outcome, but the path towards that steady state is much more tractable. Figure (4.1) describes the path towards labor market equilibrium after a disruptive innovation for both specifications.

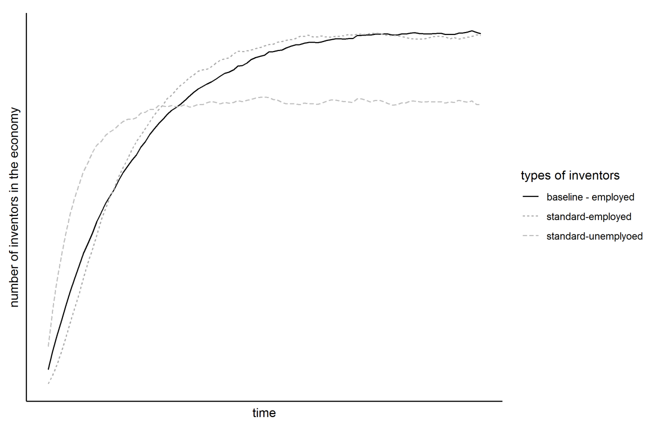

Figure 4.1: The graph shows the evolution of the number of incremental inventors in a technology cluster after its foundation. Over time, more and more inventors enter the cluster, until the steady state level is reached. The baseline specification of the model is presented in black. The grey lines depict the stock of employed and unemployed inventors in a more standard model for comparison. Such a model has slightly less employed inventors early on, because inventors enter into unemployment and leave it over time. However, not only do both models give the same kind of path qualitatively, the two paths are also quantitatively close. Assuming that inventors cannot be unemployed increases tractability without greatly changing even the quantitative results.

How many vacancies firms will create in this setting depends on the value of obtaining an additional inventor. This value is determined by the number of patents the new inventor will produce and by how much of it the firm has to pay to the inventor.

Matched pairs of inventors and firms produce patents with probability $\lambda_{f;i} = x_i * y_f$. A pair's patenting probability is the product of inventor skill and firm research quality, so matching good inventors and firms generates additional patents. Inventors leave the economy at the exogenous rate δ.

Each incremental inventor represents a stream of future patents up until he either becomes obsolete because of disruption or leaves the economy. These risks affect all incremental inventors in the same way, regardless of their patent arrival rate.

$$V_i^{inc} = \int y_f x_i V^{Patent} * e^{-rt^{t_{max}(i)}} dt = y_f x_i V^{inc}(1,1) \tag{4.3}$$

where $t_{max}(i)$ is the time the inventor becomes obsolete or leaves the economy, whichever happens first. An inventor with a higher productivity has the same risk, so the constant $y_f x_i V^{Patent}$ can be factored out. Thus, the value of any incremental inventor is a linear function of his patenting probability $y_f x_i V^{inc}(1,1)$ and the value of an inventor with skill 1 working at a firm of quality 1. I will use $V^{inc}(1,1)$ as a reference throughout the model until the equilibrium value of an inventor is solved for.

Since neither unemployed inventors nor unfilled vacancies can exist, neither side has an outside option once an inventor has drawn a specific vacancy. Thus, neither side of a match can credibly threaten the other to discard the match. Thus, the match surplus of any potential match is

$$S^{inc}(y_f, x_i) = y_f x_i * V^{inc}(1,1) \tag{4.4}$$

While they are matched, the pair expects to produce $y_f x_i$ patents. Each patent within a technology cluster c can improve firm quality and profits by the same amount, so all patents have the same value. The matched pair of firm and inventor discounts this stream of patents with the probability that the inventor leaves the economy δ, the time preference r and the probability that a disruptive invention ends the entire cluster. After matching, the pair Nash-bargains over this surplus and divides it so that firms receive share α and inventors receive $(1-\alpha)$ as wages.

The value of the additional incremental inventor i for producing firm p is

$$V_p^i(y_p, x_i) = \alpha y_p x_i * V^{inc}(1, 1) \tag{4.5}$$

The patent invention function is supermodular, so a highly skilled inventor is even more valuable for a high quality firm. Conversely, matching with a high quality firm yields more utility for a high quality inventor.

Firms create vacancies to attract inventors and gain an additional stream of patents (eq. 4.5). Just like in the standard model, firms face a congestion externality when creating their vacancies: A firm that creates another vacancy increases the number of inventors it can expect to attract and decreases the number of hires its competitors can secure. The aggregate number of new hires is fixed, because every graduate draws one random vacancy. A producing firm p gains $\frac{\eta}{N_v^{inc}}$ hires for every vacancy and pays fixed cost $\frac{1}{2} * c_v * v_p^2 * y_p$ for all its vacancies. Firms will create additional vacancies in an effort to get a larger share of the available graduates until they have driven the value of creating vacancies down to the costs:

$$c_v * v_p * y_p = \alpha * y_p \frac{1}{2} S^{inc}(1; 1) * \frac{\eta}{N_v^{inc}} \tag{4.6}$$

I.e. expected value of a new inventor for the firm $E(V(y_p; x_i))$ times the probability of obtaining an additional inventor when creating an additional vacancy $\frac{\eta}{N_v^{inc}}$ must equal the marginal costs of creating an additional vacancy $c_v * v_p * y_p$. The value of an additional inventor drives how many vacancies firms actually create, but does not influence the number of matches, since all graduates are guaranteed to draw a vacancy. The value of future hires and the number of hired inventors is independent of y_p, which is on both sides of the equation and cancels out.

Note that equation (4.6) stipulates that the number of vacancies is linear in y_p. This means that higher quality firms will create more vacancies and thus also obtain linearly more inventors at every point in time. Integrate equation (4.6) over y_p to get the average number of vacancies per firm, which yields the equilibrium number of vacancies as:

$$N_v^{inc} = (\alpha * \frac{1}{2} V^{inc}(1;1) * \frac{\eta}{c_v} N_p^{inc})^{\frac{1}{2}} \tag{4.7}$$

The number of vacancies will rise the higher the share of profits that go to firms, the higher the surplus from acquiring an additional inventor and the higher the number of firms. However, none of these factors drive up the number of vacancies linearly: Additional vacancies become less and less valuable for firms as each vacancy competes against all already existing vacancies for inventors.

The aggregate number of inventors and the rate of incremental inventions do not depend on the number of vacancies created: All inventors draw an open vacancy and will accept it. All firms create the same number of vacancies and thus receive the same number of new inventors $\frac{y_p}{N_f^{inc}}$. The aggregate rate of incremental inventions will be

$$\Lambda^{inc}(t_c) = N_i^{inc}(t_c) * \int_0^1 \int_0^1 y_p * x_i \, \mathrm{d}y_p \, \mathrm{d}x_i = \frac{\eta}{\delta}(1 - e^{-\delta t_c})\frac{1}{4} \tag{4.8}$$

where the first term describes the number of inventors at time t_c (counting time from the point in time the cluster was created through a disruptive invention). Since η inventors enter the economy at each point in time and a share δ of the existing inventors leave, this amounts to $\frac{\eta}{\delta}(1 - e^{-\delta t_c})$. The integrals describe the average productivity of the inventors of the cluster, spread evenly across firms. The distribution of inventors to firm does not change over time. More involved labor markets are certainly possible, but would not change anything fundamental about the model: A labor market such as the one described in chapter 3 would complicate the formulas, but would in the end create a similar equation to equation (4.8).

The inventor portfolio of the technology cluster grows fastest right after a disruptive invention has created the technology cluster. At this point, η matches are formed with new graduates from university, and no old matches are dissolved because none exist. All old inventors belong to the previous, now outdated technology cluster. The inventor portfolio grows more slowly over time, because more and more matches exist and the inventors in these matches leave the economy at rate δ. This dampens net growth. At $N_i^{inc}(t_c) = \frac{\eta}{\delta}$, the number of leaving and the number of entering inventors is equal. The technology cluster will reach this steady state equilibrium after an infinite time – provided no disruptive invention destroys it.

The value of all incremental inventors of firm p is defined by the aggregate rate of inventions in its technology cluster $\Lambda^{inc}(t_c)$, the share of these inventions that firm p participates in and the value of these inventions.

$$V_p^{inv} = \Lambda^{inc}(t_c) * \frac{2y_p}{N_p^{inc}} * \alpha * V^{inc}(1;1) \tag{4.9}$$

The value of producing firms is increasing in $\Lambda^{inc}(t_c)$: As the aggregate stock of inventors increases over time, producing firms will become more valuable. The higher the number of competitors N_p^{inc}, the lower the share of the overall incremental inventions made by firm p. Since y_p makes the firm's inventors more productive, it increases the share of patents that go to firm p. Higher quality firms thus have a higher stake in the incremental inventor labor market and also have a higher incentive to hinder disruptive inventions.

Since a firm with research quality 0 does not produce any patents, it will have no incentive to dampen disruptive inventions. At any point in time, there will be a marginal firm with quality y_s which is just not interested in matching with disruptive inventors and poaching them: The value gain from slowing down disruptive inventions for this firm equals the wage the firm has to pay the disruptive inventor. All firms with a research quality above this sclerosis threshold y_s will be interested in poaching disruptive inventors, while all firms with lower research quality will see poaching as a money losing proposition.

4.2.4 Labor Markets for Disruptive Inventors

Producing firms can inhibit disruptive innovation on the labor market for disruptive inventors. This is the central feature that sets my model apart from the literature. E.g., incumbent firms in Akcigit and Kerr (2018) have a portfolio of patents that is at risk from disruptions, but they have no way to prevent disruption. Labor markets provide a plausible way through which firms can hinder their competitors' innovation.

In every technology field, a stock of disruptive inventors creates disruptive inventions at rate $\Lambda^{dis}(0)$. This stock of inventors is poached by the producing firms over time and stops creating disruptive inventions. If the technology field experiences a disruption, producing firms are destroyed; disruptive inventors are freed and start disrupting again. When a disruptive inventor leaves the economy (at rate δ), a member of the same household succeeds him and matches with the last firm the leaving inventor was working for. Disruptive inventors in the each found their own disruptive firm. This reduces the complexity of the labor market for disruptive inventors without any impact on the poaching efforts of producing firms, which drive the behavior of the model.

Each disruptive inventor draws his own λ_i^{dis} from a uniform distribution between 0 and 1. Whenever a disruptive inventor is successful, he will create a new producing firm. This firm will be in the previously unavailable cluster $c+1$ and thus be worth $\omega^{c+1} f_e$: New clusters feature more valuable incremental inventions. The firm will not be a monopolist, since other firms can now enter the new cluster freely. Nonetheless, the successful disruptive inventor will effectively have gained the entry fee into the unavailable cluster.

The incentive to poach inventors on the disruptive labor markets is governed by

- the value of the portfolio of incremental inventors (eq. 4.9)
- the costs of poaching inventors
- and whether poaching causes new disruptive inventors to enter the economy (e.g. because wages for disruptive inventors increase).

To capture these three mechanisms in a simple labor market, I apply a reduced form approach. A firm that wants to poach inventors has to create vacancies. The costs of creating such vacancies rise because the different poaching firms sometimes meet on the market and because they attract additional disruptive inventors if they offer high wages to them. The cost of creating a vacancy that actually leads to a decline in Λ^{dis} thus is:

$$c_v = f_e \omega^c y_p * 1/y_s * (\frac{V(1,1)}{f_e \omega^c})^2 \tag{4.10}$$

The first term equals the costs of creating a vacancy similar to section 4.2.3. Costs rise with the returns from disruptive inventions $f_e * \omega^c$ and the research quality of the firm y_p. Hence, low and higher quality firms will again create the same number of vacancies, all else being equal.
The second term represents the congestion externality if there are many disruptive firms trying to poach inventors: With probability y_s, a producing firm will not poach on the disruptive market. The fewer producing firms actually poach, the easier it is for the remaining producing firms. E.g. if $y_s = 0.5$, half of all producing firms in the economy poach and costs double because disruptive firms will have to effectively create two vacancies to still match with the same number of disruptive inventors.
The third term represents the offer that poaching firms have to make: Producing firms have to match the wage that disruptive inventors can earn themselves in order to poach them. However, if producing firms make generous offers to disruptive inventors, it becomes more attractive to become a disruptive inventor. Additional vacancies become necessary to decrease the number of disruptive inventors as the ratio between the discounted earnings of disruptive inventors in producing firms and the current wage of disruptive inventors increases.

This setup for the careers of disruptive inventors contains two non-standard assumptions: First, that new disruptive inventors "inherit" the spot of a leaving "mentor"-inventor. As long as no producing firms interfere in the labor market, this is equivalent to the more standard "randomly drawn firm" assumption. If producing firms do interfere, this assumption does not affect the qualitative distribution of inventors, but makes the model more tractable: Since new inventors enter firms according to the currently existing distribution and not a random draw, the distribution changes slightly faster and it is not necessary to keep track of the deviation between the current distribution of disruptive inventors and a random allocation. Second, the reduced form assumptions about the labor markets for disruptive inventors are non-standard, but they make it harder for firms to poach inventors and thus work against the model mechanism. They condense the forces working against the main mechanism into an easy formula and allow me to include them into the model without it becoming intractable. This way avoids fully fleshing out a whole other labor market for inventors that are on the fence about becoming disruptive inventors or not.

To actually solve the model, I will use the guess-and-verify method of solving intertemporal optimization problems. I guess that the equilibrium path of the rate of disruptive inventions Λ^{dis} is

$$\dot{\Lambda}^{dis} = -(r + \delta + \frac{1}{2}\Lambda^{dis}) * \Lambda \tag{4.11}$$

So the rate of technology disruption goes down faster as Λ^{dis} is still high, i.e. right after a disruptive invention. As Λ^{dis} approaches zero and the risk goes down, $\dot{\Lambda}^{dis}$ converges towards 0 from above. $(r + \delta + \frac{1}{2}\Lambda^{dis})$ can be read as the rate contraction of the arrival rate of disruptive inventions.

Inserting the rate of contraction of Λ^{dis} into the value of an incremental inventor (equation 4.3) yields a value for the incremental inventor of $\frac{V^{patent} y_p x_i}{(r+\delta+\frac{1}{2}\Lambda^{dis})}$. Thus, the value of a disruptive inventor for a producing firm becomes

$$V_i^{dis}(\lambda_i^{dis}, y_p) = \lambda_i^{dis} \frac{V^{patent} y_p \frac{1}{2}}{(r + \delta + \frac{1}{2}\Lambda^{dis})^2} * [\frac{\frac{\eta}{N_p^{inc}} + \lambda_p^{inc}(\delta + r)}{(2\delta + r)(\delta + r)}] \tag{4.12}$$

I.e. the value of an incremental inventor lies in how many disruptive inventions he would have made (λ_i^{dis}) times the value gain of an incremental inventor if the rate of disruption declines (first fraction) times a weighted average of the inflow of future inventors $\frac{\eta}{N_p^{inc}}$ and the current stock of incremental inventors.

To arrive at the sclerosis threshold y_s, compare this to the expected value of getting the returns from disruptive inventions. This yields

$$y_s = \frac{1}{V_i^{dis}(1,1)} \frac{\omega f_e}{(r + \delta + \frac{1}{2}\Lambda^{dis})} \tag{4.13}$$

To see how much firms poach in equilibrium, insert equation (4.13) into equation (4.10) and compare these costs to the gains from poaching an inventor. This yields the equilibrium rate of poaching for producing firms:

$$\rho^v = \frac{1}{(r+\delta+\frac{1}{2}\Lambda^{dis})} \tag{4.14}$$

Producing firms will create additional vacancies until the probability that a vacancy leads to a successful poaching attempt is down to $\frac{1}{(r+\delta+\frac{1}{2}\Lambda^{dis})}$. Given the standard match production function ($m = (\Lambda^{dis} * v)^{\frac{1}{2}}$), the rate of poaching that disruptive inventors experience is the inverse, i.e. $\rho^{\Lambda} = (r+\delta+\frac{1}{2}\Lambda^{dis})$, which confirms the guess.

Since the rate of contraction for Λ^{dis} contains Λ^{dis}, this is a first order differential equation. Solving it yields Λ^{dis} as a function of time:

$$\Lambda^{dis}(t) = \Lambda^{dis}(0) * \frac{1-\frac{1}{2}e^{(r+\delta)c}}{e^{(r+\delta)t}-\frac{1}{2}e^{(r+\delta)c)}} \tag{4.15}$$

The equilibrium arrival rate starts at $\Lambda^{dis}(0)$ and declines over time as the denominator gets larger. In infinite time, the arrival rate will be 0. c is a constant that is fully determined by $\Lambda^{dis}(0)$.

4.2.5 Consumer Demand, Patent Value and Static Profits

Throughout the previous discussion, I assumed that patents yield a steady stream of profits equal to a constant π times the quality increase that each patent represents.

This assumption can be microfounded in a number of ways, most notably as in Akcigit and Kerr (2018). In their model, firms sell their products to a love-of-variety final goods sector and profits only depend on product quality and exogenous demand & cost parameters. As is standard in these settings, firms compete against the (appropriately weighted) average product in the market and not any specific firms. For the baseline specification of this paper, I present a close derivative of this model where I increase the role of technology clusters and introduce technology fields.

I also present an alternative specification of consumer demand that also leads to profits linear in quality. This is to emphasize that the specifics of demand do not drive my conclusions and labor markets are tractable enough so that they can be inserted in different GE-models. This alternative justification of linear profits is based on a Salop circle demand framework. In this framework, every firm competes against specific firms (its neighbors on the circle), which opens up the possibility to extend the model for strategic interactions between different firms.

Baseline specification

Consumers are part of a representative household and derive logarithmic utility from consuming a final good (Y) in continuous time. This final good is the numeraire good.

$$U = \int_0^\infty e^{-rt} \ln(Y(t))dt$$

Consumers are impatient (r). They neither face a tradeoff between leisure and consumption, nor do they experience inequality. Households evenly share income from all sources between their members.

A final goods industry produces the consumption good from labor and a variety of intermediate inputs and sells it to consumers. The industry produces according to

$$Y(t) = \frac{1}{1-\beta} L_c^\beta(t) \int_0^1 q_j^\beta z_j^{1-\beta} dj \tag{4.16}$$

where q_j is the quality of good j, z_j is its quantity and $L_c(t)$ is the labor expended in final goods production. If all product qualities are fixed, the production function exhibits constant returns to scale in labor and intermediate inputs. With increasing product qualities q_j, the production function exhibits increasing returns to scale.

Each product j corresponds to a technology field. To become a producing firm for product j, firms enter the current frontier technology cluster in that field and hire inventors.

The economy contains a mass 1 of production workers which I will call technicians. Technicians have undergone vocational training and cannot become inventors. However, they can contribute to the production of any good, regardless of the specific technology. Since all technicians are perfect substitutes and firms' research quality does not matter for production, no matching is necessary. There is a perfectly competitive spot market for technicians' labor without search costs.

The final goods industry is a price taker, consisting of a multitude of small competing firms. Hence, its inverse demand for any one intermediate good is

$$p_j = L_c^{\beta}(t) * q_j^{\beta} * z_j^{-\beta}$$

The price that the final goods industry is willing to accept for variety j of the intermediate good increases as more technicians work in the final goods industry $L_c(t)$ and the quality of the variety becomes higher. If the final goods industry buys a higher quantity z_j, the acceptable price declines.

In each of these intermediate goods sectors j, producing firms compete to satisfy this demand. They produce intermediate goods using labor:

$$z_j^f = l_j^f * \bar{q}$$

Firms use one unit of labor to produce one unit of an intermediate good of average quality.

As is standard in the literature, these firms compete in a two-stage Bertrand game: In stage one, every firm decides whether it wants to incur an arbitrarily small set-up cost ϵ to be able to produce. In stage two, all remaining firms engage in Bertrand competition. Since the result of Bertrand competition will be that only the firm with the highest quality produces, only this firm will incur the cost ϵ and it will be the monopolist in the second stage of the game.

A single monopolist with a given product quality will set the profit maximizing price and produce quantity

$$z_j^* = q_j * L_c(t)(\frac{(1-\beta)\bar{q}}{w})^{\frac{1}{\beta}} \tag{4.17}$$

Importantly, demand for the monopolist's products depends on the amount of labor employed in the final goods industry since production workers process the intermediate inputs.

The mass of small firms in the final goods sector will optimize their labor and intermediate goods intake and through this set the wage rate. Optimizing equation (4.16) with respect to labor and inserting the equilibrium on the intermediate goods market (equation 4.17) gives the optimal wage as

$$w = \beta^{\beta}(1-\beta)^{1-2\beta} * \bar{q} \tag{4.18}$$

i.e. the final goods industry will adjust its labor demand to achieve a wage rate as a multiple of the average quality $\bar{q}$ in the economy. The precise multiple is dictated by labor's output elasticity β. This behavior is optimal because the supply of intermediate varieties is itself a function of $L_c(t)$ (equation 4.17).

Producing firms make the important decisions in the model, since their decisions about hiring inventors will determine technological progress and dynamic equilibrium. However, their downstream decisions have no dynamic component: Labor input, quantity sold and price can be adjusted at any point in time. Taking into account that the final goods industry will always fix the wage rate (equation 4.18), the optimal quantity decision for a producing firm gives equilibrium profits as

$$\pi_{mon}^* = q_j * L_c(t) * (1-\beta) * \beta^{\beta}(1-\beta)^{1-2\beta} \tag{4.19}$$

Thus, a monopolist's profits are a linear function of quality and (from the viewpoint of the firm) an exogenous factor called π throughout the rest of the paper.

So far, this framework is deviating from the setup in Akcigit and Kerr (2018) in two ways: First, I introduce technology fields, equate them with products and prohibit producing firms from creating disruptive inventions. Together, these changes mean that producing firms no longer face a general threat of disruption from firms throughout the whole economy. Instead, only a distinct set of disruptive inventors within their own technology field pose a threat to producing firms.

Second, there are now multiple producing firms within one technology cluster. As in Akcigit and Kerr (2018), incremental inventions increase product quality, but I now have to make some assumptions about how producing firms split the revenues and how this is affected by new inventions. To keep the model tractable, I will assume that incremental inventions are unique, non-substitutable and additive. Hence, a producing firm that makes an incremental invention will not necessarily displace the current best product as in most ladder models, but just gain ω^c product quality. I assume that all producing firms within a technology cluster then pool all their patents to create the best possible product and split the revenues from selling that product according to the quality contribution that each firm was able to make with its patents. Since all inventions are unique and non-substitutable, market power lies with whoever holds each individual patent, who can make a take-it-or-leave-it offer to the pool of the other firms. Thus, each producing firm can extract the value of its patents, no matter which firm will actually produce.
Using the HJB, the value of the firm's patent portfolio is:

$$V(\Delta q_f) = \frac{\Delta q_f \pi}{r} \tag{4.20}$$

The value of the patent portfolio of a firm thus only depends on the impatience to consume r and Δq_f, the quality improvement that this patent portfolio makes possible. For simplicity, patents do not expire. Importantly, the value of a patent portfolio is independent of the number of researchers in any firm.

This assumption is unusual insofar as the typical quality ladder model would assume that a successful incremental invention creates a product one step above the currently existing one. Instead, in my model, an invention represents an quality improvement that any firm in the cluster could in principle use to improve their product. If the firm is not currently producing, it can license the invention to the currently producing firm to increase the quality of their product further.

Possible Alternative: Salop Circle

This section describes a completely different demand system that nevertheless gives the same result of profits being a linear function of quality. The purpose of this section is to demonstrate the flexibility of the inventor labor market setup and to showcase a setup in which firms have direct competitors which could be used for model extensions with strategic interactions between firms. To avoid confusion with the baseline specification, I will index firms f and consumers con in this section.

Consumers derive utility from a generic numeraire good a that represents consumer goods with low research content. In addition, they derive utility from satisfying a continuum of their needs located on a Salop circle of circumference 1. The needs on this circle are more advanced and can only be fulfilled with research intensive products. Needs that are located closer to each other are more substitutable. E.g., a section of the circle might represent different modes of transportation, while another section might signify entertainment. In the transportation section, one point might represent short distance trips for one person, another point might represent longer commutes and a more distant point might be intercontinental travel. Crucially, these are general needs and not existing products.
The utility function of consumer con is

$$U_{con} = \prod_{n} x_n^{\beta} * \frac{q_f}{d_{n \to f(n)}} * a_{con}^{1-\beta} \tag{4.21}$$

Utility comes from the amount of goods purchased (x_n) for each need, from the quality of the products (q_f) for each need and from the distance between this need and the product that the consumer actually bought ($d_{n \to f(n)}$). Since each point on the circle represents a need and not a product, consumers have to search for the best product to meet any specific need. The Cobb-Douglas utility function implies that consumers spend a fixed share of their income on research intensive goods, spread equally over their continuum of needs. In effect, consumers assign a constant budget to any of their needs n on the circle.
There is only a finite number of firms, each of which produces exactly one product. Firms and thus also products will be indexed with f. Firms have to position

themselves on the circle and will attract customers intent on satisfying their needs in the vicinity. E.g. a firm might decide to rent out bicycles suited for short distance trips. However, this firm's product might also be the best option for longer commutes if the bike has a high quality (e.g. an electric engine), if there are no competing products in the vicinity (e.g. because the only other transportation firm is an airline), or if the firm is charging a comparatively low price.
Consumers will buy a firm's product multiple times: They will search for the best offer for any one of their needs. E.g., consumers will search for the best firm for short trips and then again search for the best firm for commutes. The success of a firm f depends on for how many of these different needs it can make the best offer. Consumers are indifferent to a product of double the quality which is twice as far away from the desired variety. The quality and quantity of variety v are complements and the consumer derives utility from their joint consumption. Thus, the lower the price of the research intensive good, the more the consumer can buy, which again makes the quality of the research intensive good more useful to him.

From the viewpoint of firms, each need n is a separate winner-takes-all market of equal size $I * \beta$. How many of these markets a firm wins determines its revenue and size. Firms will always be able to control the markets closest to them because quality is divided by the distance of the firm to the market $\frac{q_f}{d_{n \to n}}$. Thus, any firm can offer infinite utility in the market at its location. Demand for the product of firm f is determined by the marginal market $n_{m;f;f+1}$, i.e. the market where consumers are just indifferent between product f and $f+1$ of the neighboring firm.

$$\frac{q_f}{d_{n_{m;f;f+1} \to f}} * (\frac{1}{p_f})^\beta = \frac{q_{f+1}}{d_{n_{m;f;f+1} \to f+1}} * (\frac{1}{p_{f+1}})^\beta \tag{4.22}$$

Additionally, product f competes with product $f-1$ on the other side of f. The number of markets that firm f can capture depends on the quality of its product (q_f) and the pricing and location decisions of its competitors.

In static equilibrium, firm f has to take the quality of its product as given. It first sets prices and then positions itself on the circle, considering the fixed quality of its competitors. Firm f will have to take the quality of all firms into account when setting prices, anticipating that the prices it sets will affect where its competitors position themselves.

E.g., consider a bicycle, a car and a train company all competing for markets in the transportation sector. The car company has to do research to increase the quality of the cars it can produce, set a price and then decide whether it would like to compete for short-distance inner-city trips with bicycles or for long-distance traveling with trains. Setting a low, competitive price will induce both the bicycle and the train competitor to move more into their specific niches, as will having a high quality product.

Thus, every firm owner has to position the firm taking all other variables as given. Solving equation (4.22) for the number of markets firm f captures to its left (against firm $f-1$) and to its right (against firm $f+1$) yields the profits the owner of firm f can reap:

$$\pi_f = I * \beta \frac{q_f}{p_f^\beta}[\frac{p_{f-1}^\beta d_{n_{m;f-1;f} \to f-1}}{q_{f-1}} + \frac{p_{f-1}^\beta d_{n_{m;f-1;f} \to f-1}}{q_{f-1}}](1 - \frac{mc}{p_f}) \tag{4.23}$$

Given that the firm owner has already set prices, maximizing profits now comes down to maximizing the number of markets that the firm can capture: The markup $\frac{p_f}{mc}$ is given. Note that the firm owner conceptually could influence $d_{n_{m;f-1;f}}$ by moving firm f closer to firm $f-1$ and taking its markets.

The markets that f and $f+1$ capture between them have to sum up to the distance between the two firms, so the profits of firm f can be expressed only in exogenous variables and the strategy choices of its competitors:

$$\pi_f = I * \beta[d_{f \to f+1} \frac{\frac{q_f}{p_f^\beta}}{\frac{q_f}{p_f^\beta} + \frac{q_{f+1}}{p_{f+1}^\beta}} + d_{f \to f-1} \frac{\frac{q_f}{p_f^\beta}}{\frac{q_f}{p_f^\beta} + \frac{q_{f-1}}{p_{f-1}^\beta}}](1 - \frac{mc}{p_f}) \tag{4.24}$$

where the term in brackets denotes the markets won by firm f: $d_{f \to f+1}$ is the distance between firm f and its competitor $f+1$. The two firms split the markets between them according to the ratio of the attractiveness of their products $\frac{\frac{q_f}{p_f^\beta}}{\frac{q_f}{p_f^\beta} + \frac{q_{f+1}}{p_{f+1}^\beta}}$. In the same way, firm f and firm $f-1$ share the markets between them.

From equation (4.24), it is clear that there is no Nash equilibrium if firm $f-1$ and firm $f+1$ have different qualities and prices: Firm f will always move to the firm that offers the stronger product. However, Salop circles do not have Nash equilibria in general. An equilibrium is only possible if firms take the location reaction of their competitors into account.

Consider the reactions of firm $f+1$ to the actions of firm f. Because firm $f+1$ can freely move on the circle, its profits must be independent of f. Otherwise, the firm will costlessly move to a different part of the circle. Firm $f+1$ will react to any price and quality changes of f to restore this indifference.

$$\frac{\partial \pi_{f+1}}{\partial l_f} = 0 = -\frac{\frac{q_{f+1}}{p_{f+1}^{\beta}}}{\frac{q_f}{p_f^{\beta}} + \frac{q_{f+1}}{p_{f+1}^{\beta}}} + \frac{\partial l_f}{\partial l_{f+1}} \frac{\frac{q_{f+1}}{p_{f+1}^{\beta}}}{\frac{q_f}{p_f^{\beta}} + \frac{q_{f+1}}{p_{f+1}^{\beta}}} - \frac{\partial l_{f+1}}{\partial l_f} \frac{\frac{q_{f+1}}{p_{f+1}^{\beta}}}{\frac{q_{f+1}}{p_{f+1}^{\beta}} + \frac{q_{f+2}}{p_{f+2}^{\beta}}} + \frac{\partial l_{f+2}}{\partial l_{f+1}} \frac{\frac{q_{f+1}}{p_{f+1}^{\beta}}}{\frac{q_{f+1}}{p_{f+1}^{\beta}} + \frac{q_{f+2}}{p_{f+2}^{\beta}}} \tag{4.25}$$

which yields $\frac{\partial l_{f+1}}{\partial l_f} = \frac{\partial l_{f+2}}{\partial l_{f+1}} = 1$ as the solution: If firm f moves 0.1 units closer to firm $f+1$, $f+1$ will also move 0.1 units towards $f+2$. Firm $f+1$ can do this because it expects firm $f+2$ (and $f+3$, $f+4$,...) to do the same, restoring the original positioning.

Now consider the case where firm f has set a higher price. Again, firm $f+1$ cannot profit from that, since otherwise firms from other parts of the circle would move to the spot of firm $f+1$: $\frac{\partial \pi_{f+1}}{\partial p_f} = 0$. Thus,

$$\frac{\partial d_{f \to f+1}}{\partial p_f} = -\beta p_f^{-\beta} * \frac{\frac{q_f}{p_f^{\beta}}}{\frac{q_f}{p_f^{\beta}} + \frac{q_{f+1}}{p_{f+1}^{\beta}}} \tag{4.26}$$

I.e., by increasing its price, firm f captures a slightly smaller share of the markets between f and $f+1$. $f+1$ then moves closer so as to exactly maintain the number of markets it captures itself. Two firms share the markets between them according to the ratio of the attractiveness of their products. So when f becomes less attractive because of price increases, firm $f+1$ has to move closer to shorten the distance between the two firms. If the price of product f was already high, f only has a tiny share of the contested markets and additional price increases only require small changes in location. Even though this movement lowers its profits, firm $f+1$ has to do this to protect itself against other firms moving into the resulting gap.

Equations (4.25) and (4.26) imply that the utility of the marginal consumer between two firms is constant across the economy. Intuitively, this follows more or less directly from the free movement condition: Since the profits of firm f depend directly on its own quality, its price and the utility of the marginal consumers it can still capture (4.23), it stands to reason that one spot on the circle cannot have marginal consumers with higher utility, since firms would otherwise move there. Thus, I denote the sum of the utility of the two marginal consumers of each firm as **C**. **C** is a competition parameter describing how low firms have to set prices to stave off competing firms. It rises with how many firms of a given quality are in the economy.

Mathematically, inserting **C** into equation (4.23), firm profits are

$$\pi_f = I\beta D_f - I\beta D_f^{(1+\frac{1}{\beta})}[\mathbf{C}]^{\frac{1}{\beta}} q_f^{\frac{-1}{\beta}} \frac{mc}{\beta} \tag{4.27}$$

where D_f denotes the number of captured markets, i.e. the number of markets for which the product of f is the best product. Firms earn $I\beta$ per captured market, but the costs of servicing these markets increase non-linearly, because lowering prices forces a firm to serve its already captured markets with more produce or leave revenue on the table. Equation (4.27) takes into account that firm f expects its neighboring firms to keep their profits and thus the fractions in equation (4.23) constant. Thus, if f increases its price, f expects the other firms to move closer, tightening competition compared to equation (4.24). Likewise, if firm f decreases its price, it expects to cater to additional markets partly because its direct competitors move away and partly because its products become more attractive.

Maximizing equation (4.27) yields

$$p_f = (1 + \frac{1}{\beta})mc \tag{4.28}$$

for the optimal price: Firms charge a fixed markup over marginal costs depending on the demand parameter β, which denotes how long additional quantity still generates value for the customers for any given variety. If additional quantity does not lead to much additional utility, firms cannot gain many customers by lowering prices and charge a high markup.

Given this pricing behavior, customers search for the best product for each different variety. This yields the number of varieties serviced by each firm as

$$D_f = q_f \beta [\frac{1}{(1+\beta)mc}]^{\beta} [\mathbf{C}] \tag{4.29}$$

Serviced markets are a linear function of a firm's quality, given that every firm charges the same price, regardless of its quantity. The number of markets served reacts more strongly to quality if the marginal costs are small, so that the costs of serving additional markets do not matter so much. The effect of the demand parameter β is more ambiguous, because a high β raises the costs of servicing a new market (because consumers demand more goods), but also means that consumers spend more in each market. Firms leverage their quality to service more markets, not to raise their prices. Since the circumference of the Salop circle is finite, this is a predatory strategy: High quality firms push out their competitors.

Since only the number of served markets rises with quality, profits are also linear in quality:

$$\pi_f = D_f * I\beta * \frac{1}{1+\beta} = q_f [\frac{\beta}{(1+\beta)mc}]^{\beta} [\mathbf{C}] I\beta \frac{1}{(1+\beta)} \tag{4.30}$$

Every firm faces the same marginal costs and charges the same price, thus profits in every market are the same ($I\beta * \frac{1}{1+\beta}$). Profits per market are higher if β increases, because consumers allot a higher budget to each need. This is partly counteracted because a higher β also means that consumers draw more utility from the quantity that firms produce, which harms firms: Since consumers value lower prices, firms try to steal each others' markets by lowering prices. Yet, the higher overall spending for the research intensive good prevails.

Equilibrium requires that the whole circle is serviced, i.e. $\sum D_f = 1$. This allows to solve for the equilibrium value of competition strength $[\mathbf{C}] = \frac{1}{\sum {q_f}_f}(1+\beta)^\beta mc^\beta$. The strength of equilibrium competition is rising in the sum of all qualities of active firms: Since every firm captures markets on the Salop circle in relation to their quality, if there are more high quality firms, every firm has to receive a smaller number of markets. Marginal costs lower the competition each firm feels, because higher marginal costs decrease the incentive for each firm to spread out over multiple markets. Given the level of competition, firms can cater to $q_f * \sum {q_f}_f^{-1}$ markets. Consequently, every firm makes profits of $q_f * \sum {q_f}_f^{-1} I\beta(1+\beta)^{-1}$.

The economy is closed by the labor market and the market for the numeraire good. The economy produces the numeraire good with the fixed amount of labor L with the technology of all firms $\sum q_f$. Thus, the research intensive sector increases the productivity of the numeraire sector. Since the numeraire sector is competitive, its whole revenue is earned by its laborers. Thus, the equilibrium income in the economy is

$$I = \sum q_f L(1+\beta) \tag{4.31}$$

i.e., the labor income from the numeraire sector plus the profits from the firms in the research intensive sector. Labor income increases the higher the productivity of the economy and the more labor L households supply. The higher β, the higher the profit share of the economy, as well as nominal income for a given productivity level. However, a higher β would also lead to higher prices for the research intensive good, so real income is not rising.

Given this nominal income level, the profit of any given firm is

$$\pi_f = q_f * \beta \tag{4.32}$$

and thus is only a function of a firm's product quality q_f and the constant parameter β. However, potential entrants do not only care about current conditions, but are motivated by potential future profits. Thus, the number of firms in equilibrium is determined by future prospects for quality improvements through research.

Within a cluster currently at the technology frontier, i.e. a cluster that is the best in its field, patents improve the product quality of firms and thus represent a steady stream of profits for the firm that holds them. The value of a patent

$$V(p_c) = \omega^c * \frac{\beta}{r} \tag{4.33}$$

is a function of parameters of the model and thus fixed. It rises with c, as patents in more advanced clusters create more quality (parameter ω determines the strength of this effect). The value of a patent also rises in β, which governs the markups of firms and the amount of money consumers spend on the research intensive good.

Given this value of patents, the value of an inventor is the stream of patents he represents. The value of the inventor portfolio of all firms with a given quality y_f is thus

$$V_f(N_i^c(y_f, x_i, t_c^e)) = \int_0^1 (V(p_c) y_f x_i (1 - e^{-t_c^e}) \frac{2\eta}{\delta r} \,\mathrm{d}x_i = y_f V_f(N_i^c(y_f = 1, t_c^e)) \tag{4.34}$$

I.e. the value of the patent portfolio of firms is increasing in y_f because high quality firms produce more patents with the inventors they have. The value of a firm's patent portfolio increases as long as the current technology cluster is still on the edge and additional inventors are still entering the cluster.

A potential entrant does not have an inventor portfolio, but expects to hire inventors in the future. The value of this stream is dependent on the research quality y_f the entrant will draw.

$$V_f(y_f) = \frac{1}{N_f(y)} \int_0^1 (\eta x_i * V_f(y_f; x_i) \,\mathrm{d}x_i \frac{1}{r + \Lambda_{dis}} = y_f V_f(y_f = 1) \tag{4.35}$$

The stream of inventors matched with firms of quality y is shared between all firms of that quality $\frac{1}{N_f(y)}$. Again, the value of the stream of hires is increasing in y_f because a higher quality firm gets more patents out of each hire. If the value of a patent in the technology cluster $V(p_c)$ is higher, firms value the stream of inventors they will hire more. The share of profits flowing to the firm makes future inventors more valuable, too. The likelihood of disruptive inventions decreases the value of future inventors: If a disruptive invention occurs, new inventors will not enter the now obsolete cluster of the firm. The stream of hires will dry up.

Whenever a new technology cluster is created (and only then), new firms can enter. New firms entering the economy do not yet have inventors or patents. However, entrants gain access to the inventor labor market and will hire inventors and produce patents in the future. Firms pay an entry fee f_e to become experts in a technology cluster proportional to ω^c: The more disruptive inventions were necessary to form the cluster, the more sophisticated the technology is and the more setup is necessary. In equilibrium, the ex ante expected value of future hired inventors must equal this setup cost. Thus,

$$N_f = \eta \frac{2}{9} f_e \frac{\beta}{r} \frac{\alpha}{r+\delta} \frac{1}{r+\Lambda_{dis}} \tag{4.36}$$

Since entrants draw a quality y_f randomly from a uniform distribution between 0 and 1, there is an equal mass of entrants (and firms) at every quality $N_f(y)$. The expected value of entry declines as more firms enter, because a higher number of entrants compete for a fixed number of graduates. However, the value of entry is independent of patents or the inventors already in the cluster. Hence, firms will enter as soon as the disruptive invention creates the cluster and drive the expected returns from entering down to the entry fee f_e.

Some firms will ex post regret entering: They draw a bad research quality and do not make enough profits to recoup their entry costs. Using equation (4.35), ex post profits are $3y_f f_e$. Thus, all firms that draw a quality of $\frac{1}{\sqrt{3}} = 0.58$ or worse will not recoup f_e. These firms will not exist, since there is no continuous cost of operation apart from inventor wages. Thus, such firms will participate in the search for inventors and hire those with which they can recover at least some part of their entry fee.

4.2.6 Technological Progress

Technological progress in the economy is twofold: Incremental inventions improve the average quality of the products in the economy and ultimatively increase the utility of consumers. Disruptive progress increases the value of future incremental progress. In equilibrium, disruptive innovation declines from the maximum to 0, while the number of incremental inventions converges from 0 to the maximum. In equilibrium, the economy still grows as new incremental inventions increase quality, but economic growth as a percentage of GDP declines because incremental inventions can only create linear growth.

Each frontier technology cluster in each technology field faces a chance of disruption Λ^{dis}, upon which a new, more valuable technology cluster emerges. The rate of disruptive inventions is declining as more and more disruptive inventors get poached by producing firms (4.15). For any specific technology field, this creates a saw blade like graph of the rate of disruption (Figure 4.2).

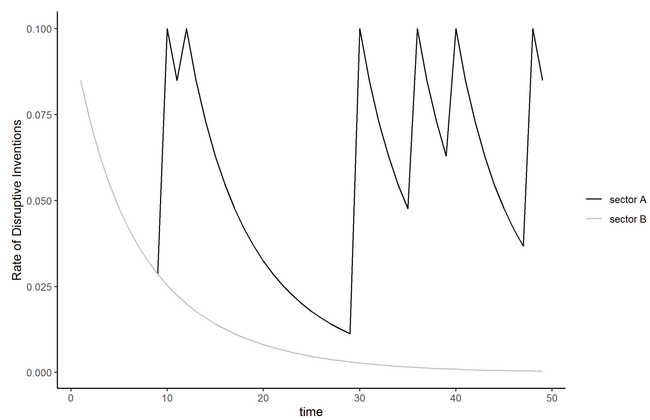

Figure 4.2: Example of the path of two technology fields or sectors of the economy. Sector A experienced several disruptive inventions which create a saw blade pattern: After every disruptive invention, all producing firms close down and poached disruptive inventors become active again. The probability for further disruptive inventions goes up to the maximum rate again. Then producing firms start poaching inventors again to decrease this rate. Sector B did not make a disruptive invention at the beginning and the chances decreased as time went on, because most disruptive inventors were already poached. In the end, the sector did not experience any disruptive inventions before it arrived at the no-disruption equilibrium.

The whole economy consists of many such sectors and is thus not subject to the randomness of any one sector. The expected change in Λ^{dis} for any one technology field or sector is

$$E(\Delta\Lambda^{dis}) = \Lambda^{dis}(\Lambda^{dis}(0) - \Lambda^{dis}) - \Lambda^{dis}(r + \delta + \frac{1}{2}\Lambda^{dis}) \tag{4.37}$$

The first term describes that with probability Λ^{dis}, a disruptive invention will occur and set Λ^{dis} to $\Lambda^{dis}(0)$. The second term encapsulates the poaching efforts of producing firms, which will decrease the rate of disruptive inventions by $\Lambda^{dis}(r + \delta + \frac{1}{2}\Lambda^{dis})$. Note that the rate of disruptive inventions is clearly declining for every value of Λ^{dis} as long as $\Lambda^{dis}(0) < r + \delta$. This restriction will hold in most real world applications: Hobijn and Şahin (2009) estimate a separation rate of around 1.5% for the average OECD country, which together with a real interest rate of a conservative 2% would imply that the average sector of the economy stays undisrupted for 18 years or more. Even if this parameter restriction is violated, the qualitative result remains, but it becomes much harder to show analytically. Appendix I details the results of the empirical simulation.

The exact parameters notwithstanding, it is clear from equation (4.37) that the only possible equilibrium for any one sector is that the rate of disruptive inventions is zero: It is the only point where both the expected change and the change in case of no disruptive inventions are zero, so the technology field will never leave this point. Any technology field will thus eventually experience the decline of disruptive inventions to zero, even if $\Lambda^{dis}(0)$ is very high. More and more technology fields will be stuck in this equilibrium, until eventually all of them are.

Nevertheless, incremental inventors will add to the product quality of producing firms at each point in time. How much quality they add to the economy depends on the technology cluster they are in: Technology fields with large inventor portfolios and more disruptive inventions in the past will contribute more quality increases (equation 4.8). Technological progress through incremental invention in one technology field then is

$$\Delta q_c(t_c^e) = \frac{\eta}{\delta}(1 - e^{-t_c^e})\frac{1}{6} * \omega^c \tag{4.38}$$

I.e., progress is a function of the number of inventors in that cluster and the quality increase that an incremental invention in the frontier cluster of the field creates.

Technological progress in a field changes as additional inventors enter the field, old inventors leave and disruptive inventions make the whole stock of inventors obsolete:

$$E(\Delta \dot{q_c}(t_c^e)) = \omega^c * \eta \frac{1}{6} - \delta \Delta q_c(t_c^e) - \Lambda^{dis} \Delta q_c(t_c^e) \tag{4.39}$$

If no disruptive invention happens, the frontier cluster will eventually absorb all inventors in the field. At this point, technological progress will be linear, as each inventor produces a set amount of inventions, each of which adds a fixed amount of quality ω^c. This is the steady state outcome: The rate of disruption will eventually decline to 0 and after that, all inventors will eventually work in that cluster as $(t_c^e) \to \infty$.

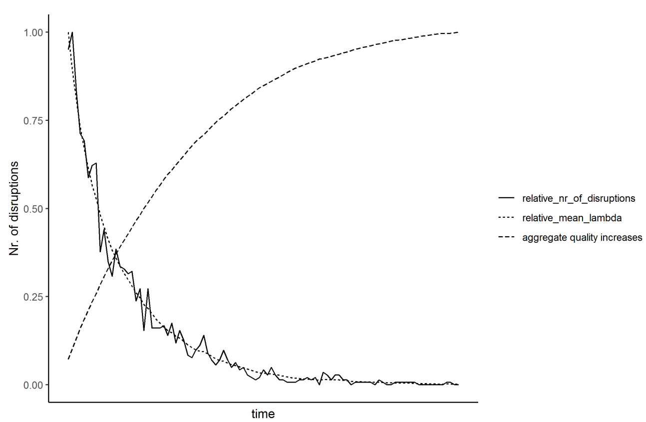

Figure 4.3: The path towards the steady state of the economy. The solid black line denotes the number of disruptive inventions at each point in time for a simulated economy with 2000 sectors. The dotted line denotes the theoretically expected number. Evidently, while there is still some randomness, the actual number of inventions tracks the predicted line quite closely. The rate of disruptive inventions decreases as more and more disruptive inventors get poached by producing firms. As that happens, the aggregate rate of quality growth in the economy slows down until linear growth is reached in the steady state.

4.3 Description of Equilibrium and Policy Implications

The economy presented in the baseline specification has several major decision points, only some of which the market economy handles efficiently.

First, there is the demand of the final goods sector for intermediate products to turn into the final consumer product. The economy has a fixed number of products defined by how many technology fields there are and all of them are produced in equilibrium. However, the quantity produced is smaller than in the optimum because of the monopoly power of intermediate goods producers. This inefficiency depresses output by a fixed share, but has no impact on equilibrium growth rates.

Second, intermediate goods producers have to hire incremental inventors to improve their product. Producers hire all incremental inventors by assumption (because new graduates are guaranteed to draw a job). So, there is no inefficiency in this dimension.

Third, disruptive inventors work on disrupting the economy and get poached by producing firms to prevent this. The market economy weighs the costs of disruptive inventions against the entry costs for producing firms: A successful disruptive inventor is not able to appropriate all the benefits from his invention as profits because other entrepreneurs can enter the new technology cluster that he has created. Producing firms bear all costs from disruption and receive none of the benefits, thus they have a strong incentive to prevent disruption. A social planner that maximizes the utility of representative households makes a very different calculation: He weighs the value of getting graduates empowered by the disruptive invention in the future against the costs of losing all current inventors:

$$\int \frac{1}{4}\eta V_i^{inc}(t)e^{-rt}\,\mathrm{d}t \geq \frac{V^{patent}\Lambda^{inc}(t)}{(r+\delta+\frac{1}{2}\Lambda^{dis})} \tag{4.40}$$

Firms do not make this calculation since the value of the future inventors that other firms will get does not factor into their profits. It is apparent that a social planner might even arrive at the same conclusion as the market economy if the discount rate is sufficiently high: Empowering future graduates takes longer to pay off than current incremental inventions.

This highlights an important point about the tradeoffs involved in the decision about which type of research to pursue: Increasing long run economic growth in this model requires unambiguously hurting the current generation. The currently living incremental inventors and firms have a vested interest in slowing economic growth. Fast productivity growth through disruption does not benefit them, but the inventors and firms who will enter the newly created cluster. A social planner might want to solve this via transfers, but even that might not work: The current stock of incremental inventors is made obsolete, temporarily decreasing GDP. While it will eventually be rebuilt and growth will increase, many incremental inventors and firm owners that were hurt by the disruption will already have left the economy. Effectively, the current generations prefer to increase the level of economic activity through incremental inventions at the cost of economic growth. Of course, the linear technological progress of incremental improvements is still progress, but it means that the growth rate of the economy will continuously decline.

If the social planner wants to preserve the arrival rate of disruptive inventions in the economy, he has to slow down the rate at which producing firms poach disruptive inventors. There are in principle two ways to achieve this: One is to decrease the value of the stock of incremental inventors, which decreases the incentive to poach. Increasing the separation rate of inventors and firms or decreasing the market power that firms enjoy on the goods market would both work in this direction. However, these are large interventions into the markets. The second route is to decrease the ability of large producing firms to poach disruptive inventors. An easy step in this direction would be to restrict startup acquisitions significantly. There is an active literature on the questions of whether startup acquisitions are welfare enhancing (Cabral, 2018; Piazza and Zheng, 2019). My paper offers an additional argument for prohibiting such acquisitions.

Income in the economy is derived from the wages of technicians, the profits of firms and the wages of incremental and disruptive inventors. As in the base model of Akcigit and Kerr (2018), the revenue of producing firms within each technology field/product is constant. Of that revenue, a fixed share goes to technicians pay for labor input into production. The remainder pays the rents of firms and their investments into inventors.

Firms pay out a fixed share α of the quality increases that incremental inventions produce to their incremental inventors. If firms hire disruptive inventors, they pay them out of their share $1-\alpha$. This reduces their stream of profits, but increases the expected duration of this stream. Poaching disruptive inventors is only profitable if the expected profits of disruptive inventors ($\Lambda^{dis}\omega^c f_e$) are smaller than what firms can earn from incremental inventions ($(1-\alpha)\Lambda^{inc}V^{Patent}$). Otherwise, equation (4.13) will yield a sclerosis threshold larger than 1 and no firms will actually poach inventors.

4.4 Conclusion

As productivity growth is declining across frontier economies, it is urgent to understand firm innovation as a determinant of productivity development. This study offers a general equilibrium framework to analyze how inventors and firms match and which research avenues firms pursue. In a search and matching labor market, firms have to acquire expertise in a technology and then build and protect a portfolio of specialized inventors to do research. Thus, producing firms are invested in existing technologies and resist disruptive inventions that might make their own technology obsolete. Firms can impede disruptive technology growth either by outright buying disruptive firms or by poaching the inventors disruptive startups need. Firms focus on incremental improvements that increase the quality of their product, but do not change the general technology structure.

The model describes the situation found in empirical work well: Section 3.4 documents that technology clusters are dominated by very few firms. The model predicts that firms that impede disruptive innovation hire more inventors and pursue smaller, more incremental inventions. Thus, patent counts rise and productivity growth falls. Poege et al. (2019) and Akcigit and Kerr (2018) have grouped patents into incremental improvements and more radical innovation using the quality of scientific literature linked to the patent and the citations from other firms. Both have found that more ambitious patents are more valuable to the applicant. Despite that, firms' research has become more incremental (Arora et al., 2019). Firms produce more and more patents with an increasing number of researchers, whose productivity is falling, yet whose wages do not decrease (Cowen and Southwood, 2019; Bloom et al., 2017). My model offers a reinterpretation of this finding: Firms might decide to only look for incremental improvements as a strategy to protect their rents. However, creating exponential growth with incremental improvements is indeed getting harder and harder. As a result, there might be a troublesome misallocation of inventive talent to incremental innovation with declining returns.

The model implies several levers for policy intervention: One example is banning the acquisition of startups. Such regulation, while difficult to codify and enforce, would prohibit large firms from monopolizing research talent and inhibiting technology disruption. This is equivalent to making it more difficult to poach disruptive inventors in my model. Extending merger controls to labor markets has been suggested e.g. by Naidu et al. (2018), but for different reasons than the ones presented here. However, there have also been arguments in favor of startup buyouts. Among others, Cabral (2018) argues that allowing incumbents to buy startups can increase the incentive to innovate: Potential entrepreneurs should start more innovative firms because they expect to sell to big corporations. This argument need not even hold in traditional endogenous growth models, where the amount of research alone determines growth (Piazza and Zheng, 2019). If different types of innovation exist, the argument breaks down: Large firms can also acquire startups to suppress disruptive innovation and redirect R&D into incremental research.

My model's implications for inventor mobility are less clear cut: Since the production function is supermodular, sorting all inventors to the best firm yields more incremental patents. In this sense, e.g. improving the search technology is beneficial. Hence, strong assortative matching increases short-run growth. However, strong assortative matching also implies large monopoly profits for high quality producing firms, who will then oppose disruptive inventions. The exact effect depends on which actions these firms can take, but long-run growth will decline. Optimal policy could target the search technology to disperse inventors more widely among firms or levy taxes that increase with a firm's share of patents in any technology cluster.

Apart from these results, the paper also makes a technical contribution by demonstrating how an elementary search and matching labor market can be inserted into a general equilibrium model without greatly increasing its complexity. Given that the equilibria in search and matching models are most often found through numerical simulation (Rogerson et al., 2005; Hagedorn et al., 2017), this represents a significant step in its own right.

Chapter 5

Summary

My dissertation consists of three studies, all viewing aggregate productivity as driven by the individual decisions of firms and the inventors that work for them. I use microeconometric analysis to study why firms innovate and economic theory to link these decisions to macroeconomic outcomes.

The first paper in this dissertation studies how German manufacturing firms adjust their productivity in response to an increase in competition from foreign markets. German firms only increase their productivity if their new competitors come from other industrialized economies. This productivity increase is not driven by innovation. Instead, firms cut input expenses and prices while maintaining their output.

The second paper traces the matching decisions of firms and inventors on the labor markets of developed economies. It adapts empirical techniques used in labor economics to this special segment of the labor market and shows that assortative matching has been increasing from 1974 to 2012: High quality inventors go to high quality firms more often than was the case in previous decades. This cannot be explained by changes in the patent invention function: The productivity of a match between a firm and an inventor of constant quality remains roughly unchanged.

The third paper develops an endogenous growth model with inventor labor markets and two types of innovation: disruptive inventions that change the under-

lying technology of firms' products and incremental improvements over existing products. Firms acquire expertise in certain technologies by hiring the inventors who are experts in these fields. This gives them a strong incentive to prevent disruptive inventions: If the underlying technology changes, their investment in these inventors becomes worthless. Large firms inhibit aggregate growth by poaching inventors from firms engaged in disruptive innovation.

Bibliography

Abowd, J.M., Kramarz, F., Margolis, D.N., 1999. High Wage Workers and High Wage Firms. Econometrica 67, 251–333. doi:10.1111/1468-0262.00020.

Abramovitz, M., 1956. Resource and Output Trends in the United States Since 1870. NBER Chapters. National Bureau of Economic Research, Inc.

Aghion, P., 1998. Endogenous Growth Theory. The MIT Press.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and Innovation: An Inverted-U Relationship. The Quarterly Journal of Economics 120, 701–728. doi:10.1093/qje/120.2.701.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., Prantl, S., 2004. Entry and Productivity Growth: Evidence from Microlevel Panel Data. Journal of the European Economic Association 2, 265–276. doi:10.1162/154247604323067970.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., Prantl, S., 2009. The Effects of Entry on Incumbent Innovation and Productivity. The Review of Economics and Statistics 91, 20–32.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., Van Reenen, J., 2016. Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. Journal of Political Economy 124, 1–51. doi:10.1086/684581.

Aghion, P., Griffith, R., Howitt, P., 2006. U-shaped relationship between vertical integration and competition: Theory and evidence. International Journal of Economic Theory 2, 351–363.

Aghion, P., Howitt, P., 1992. A Model of Growth Through Creative Destruction. Econometrica 60, 323–351. doi:10.2307/2951599.

Akcigit, U., Ates, S.T., 2019. What Happened to U.S. Business Dynamism? Technical Report. Working Paper.

Akcigit, U., Caicedo, S., Miguelez, E., Stantcheva, S., Sterzi, V., 2018. Dancing with the Stars: Innovation Through Interactions. Working Paper 24466. National Bureau of Economic Research. doi:10.3386/w24466.

Akcigit, U., Kerr, W.R., 2018. Growth through Heterogeneous Innovations. Journal of Political Economy 126, 1374–1443.

Amiti, M., Konings, J., 2007. Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. The American Economic Review 97, 1611–1638.

Andrews, D., Criscuolo, C., Gal, P., 2016. The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy. OECD Productivity Working Papers 5. doi:10.1787/63629cc9-en.

Andrews, M.J., Gill, L., Schank, T., Upward, R., 2008. High wage workers and low wage firms: Negative assortative matching or limited mobility bias? Journal of the Royal Statistical Society: Series A (Statistics in Society) 171, 673–697. doi:10.1111/j.1467-985X.2007.00533.x.

Andrews, M.J., Gill, L., Schank, T., Upward, R., 2012. High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias. Economics Letters 117, 824–827. doi:10.1016/j.econlet.2012.07.033.

Arkolakis, C., Papageorgiou, T., Timoshenko, O.A., 2018. Firm learning and growth. Review of Economic Dynamics 27, 146–168. doi:10.1016/j.red.2017.06.001.

Arora, A., Belenzon, S., Patacconi, A., Suh, J., 2019. The Changing Structure of American Innovation: Some Cautionary Remarks for Economic Growth. Working Paper 25893. National Bureau of Economic Research. doi:10.3386/w25893.

Autor, D., Dorn, D., Hanson, G., Pisano, G., Shu, P., 2016. Foreign Competition and Domestic Innovation: Evidence from U.S. Patents. Technical

Report w22879. National Bureau of Economic Research. Cambridge, MA. doi:10.3386/w22879.

Autor, D., Dorn, D., Katz, L.F., Patterson, C., Van Reenen, J., 2017. The Fall of the Labor Share and the Rise of Superstar Firms. Working Paper 23396. National Bureau of Economic Research. doi:10.3386/w23396.

Autor, D.H., Dorn, D., Hanson, G.H., 2013. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. American Economic Review 103, 2121–2168. doi:10.1257/aer.103.6.2121.

Aw, B.Y., Roberts, M.J., Xu, D.Y., 2011. R&D Investment, Exporting, and Productivity Dynamics. American Economic Review 101, 1312–1344. doi:10.1257/aer.101.4.1312.

Barkai, S., 2017. Declining Labor and Capital Shares. Working Paper .

Bernard, A.B., Eaton, J., Jensen, J.B., Kortum, S., 2003. Plants and Productivity in International Trade. American Economic Review 93, 1268–1290. doi:10.1257/000282803769206296.

Bernard, A.B., Jensen, J.B., Schott, P.K., 2006. Trade costs, firms and productivity. Journal of Monetary Economics 53, 917–937. doi:10.1016/j.jmoneco.2006.05.001.

Bessen, J., Maskin, E., 2009. Sequential innovation, patents, and imitation. The RAND Journal of Economics 40, 611–635. doi:10.1111/j.1756-2171.2009.00081.x.

Beveren, I.V., 2012. Total Factor Productivity Estimation: A Practical Review. Journal of Economic Surveys 26, 98–128. doi:10.1111/j.1467-6419.2010.00631.x.

Biggerstaff, L., Cicero, D.C., Puckett, A., 2016. FORE! An Analysis of CEO Shirking. Management Science 63, 2302–2322. doi:10.1287/mnsc.2016.2452.

Bloom, N., Draca, M., Van Reenen, J., 2016. Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. The Review of Economic Studies 83, 87–117. doi:10.1093/restud/rdv039.

Bloom, N., Genakos, C., Sadun, R., Van Reenen, J., 2012. Management Practices Across Firms and Countries. Academy of Management Perspectives 26, 12–33. doi:10.5465/amp.2011.0077.

Bloom, N., Jones, C.I., Van Reenen, J., Webb, M., 2017. Are Ideas Getting Harder to Find? Working Paper 23782. National Bureau of Economic Research. doi:10.3386/w23782.

Bloom, N., Propper, C., Seiler, S., Reenen, J.V., 2015. The Impact of Competition on Management Quality: Evidence from Public Hospitals. Review of Economic Studies 82, 457–489.

Bloom, N., Van Reenen, J., 2010. Why Do Management Practices Differ Across Firms and Countries? SSRN Scholarly Paper ID 1533440. Social Science Research Network. Rochester, NY.

Bonhomme, S., Lamadon, T., Manresa, E., 2017. A Distributional Framework for Matched Employer Employee Data. SSRN Scholarly Paper ID 3333421. Social Science Research Network. Rochester, NY.

Borenstein, S., Farrell, J., 2000. Is Cost-Cutting Evidence of X-Inefficiency? American Economic Review 90, 224–227. doi:10.1257/aer.90.2.224.

Borovičková, K., Shimer, R., 2017. High Wage Workers Work for High Wage Firms. Technical Report 24074. National Bureau of Economic Research, Inc.

Breitmoser, Y., Tan, J.H.W., Zizzo, D.J., 2010. Understanding perpetual R&D races. Econ Theory 44, 445–467. doi:10.1007/s00199-009-0487-4.

Bresnahan, T.F., Trajtenberg, M., 1995. General purpose technologies 'Engines of growth'? Journal of Econometrics 65, 83–108. doi:10.1016/0304-4076(94)01598-T.

Bretschger, L., Lechthaler, F., Rausch, S., Zhang, L., 2017. Knowledge diffusion, endogenous growth, and the costs of global climate policy. European Economic Review 93, 47–72. doi:10.1016/j.euroecorev.2016.11.012.

Bryan, K.A., Lemus, J., 2017. The direction of innovation. Journal of Economic Theory 172, 247–272. doi:10.1016/j.jet.2017.09.005.

Cabral, L.M.B., 2018. Standing on the Shoulders of Dwarfs: Dominant Firms and Innovation Incentives. Technical Report 13115. C.E.P.R. Discussion Papers.

Card, D., Heining, J., Kline, P., 2013. Workplace Heterogeneity and the Rise of West German Wage Inequality. The Quarterly Journal of Economics 128, 967–1015.

Comin, D., Mestieri, M., 2018. If Technology Has Arrived Everywhere, Why Has Income Diverged? American Economic Journal: Macroeconomics 10, 137–178. doi:10.1257/mac.20150175.

Comin, D.A., Mestieri, M., 2010. An Intensive Exploration of Technology Diffusion. Technical Report 16379. National Bureau of Economic Research, Inc.

Cowen, T., 2011. The Great Stagnation: How America Ate All The Low-Hanging Fruit of Modern History, Got Sick, and Will (Eventually) Feel Better. Dutton.

Cowen, T., Southwood, B., 2019. Is the rate of scientific progress slowing down? Unpublished Manuscript .

Crepon, B., Duguet, E., Mairesse, J., 1998. Research, Innovation And Productivity: An Econometric Analysis At The Firm Level. Economics of Innovation and New Technology 7, 115–158.

Dauth, W., Findeisen, S., Suedekum, J., 2014. The Rise of the East and the Far East: German Labor Markets and Trade Integration. Journal of the European Economic Association 12, 1643–1675.

De Loecker, J., 2011. Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity. Econometrica 79, 1407–1451. doi:10.3982/ECTA7617.

De Loecker, J., Eeckhout, J., 2017. The Rise of Market Power and the Macroeconomic Implications. Working Paper 23687. National Bureau of Economic Research. doi:10.3386/w23687.

De Loecker, J., Goldberg, P.K., 2014. Firm Performance in a Global Market. Annual Review of Economics 6, 201–227. doi:10.1146/annurev-economics-080113-104741.

De Loecker, J., Goldberg, P.K., Khandelwal, A.K., Pavcnik, N., 2016. Prices, Markups, and Trade Reform. Econometrica 84, 445–510. doi:10.3982/ECTA11042.

Denicolò, V., 2000. Two-Stage Patent Races and Patent Policy. SSRN Scholarly Paper ID 235286. Social Science Research Network. Rochester, NY.

Dhyne, E., Petrin, A., Smeets, V., Warzynski, F., 2017. Multi Product Firms, Import Competition, and the Evolution of Firm-Product Technical Efficiencies. Working Paper 23637. National Bureau of Economic Research. doi:10.3386/w23637.

Doraszelski, U., Jamandreu, J., 2013. R&D and Productivity: Estimating Endogenous Productivity. The Review of Economic Studies 80, 1338–1383.

Eslava, M., Haltiwanger, J., Kugler, A., Kugler, M., 2004. The effects of structural reforms on productivity and profitability enhancing reallocation: Evidence from Colombia. Journal of Development Economics 75, 333–371. doi:10.1016/j.jdeveco.2004.06.002.

Fosfuri, A., Motta, M., Rønde, T., 2001. Foreign direct investment and spillovers through workers' mobility. Journal of International Economics 53, 205–222. doi:10.1016/S0022-1996(00)00069-6.

Foster, L., Haltiwanger, J., Syverson, C., 2008. Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? The American Economic Review 98, 394–425.

Gal, P., 2017. Essays on the Role of Frictions for Firms, Sectors and the Macroeconomy. Tinbergen Institute.

Gal, P.N., Andrews, D., Criscuolo, C., 2016. The Global Productivity Slowdown, Technology Divergence, and Public Policy: A Firm Level Perspective.

Gaure, S., 2014. Correlation bias correction in two-way fixed-effects linear regression. Stat 3, 379–390. doi:10.1002/sta4.68.

Gordon, R.J., 2016. The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War. 1st edition edition ed., Princeton University Press, Princeton Oxford.

Hagedorn, M., Law, T.H., Manovskii, I., 2017. Identifying Equilibrium Models of Labor Market Sorting. Econometrica 85, 29–65. doi:10.3982/ECTA11301.

Hall, B.H., Ziedonis, R.H., 2001. The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. The RAND Journal of Economics 32, 101–128. doi:10.2307/2696400.

Harhoff, D., 1997. Incentives to Innovate: A Structural Model of Oligopoly (Available Only in German!). Technical Report FS IV 97-09. Wissenschaftszentrum Berlin (WZB), Research Unit: Competition and Innovation (CIG).

Helpman, E., Trajtenberg, M., 1998. Diffusion of General Purpose Technologies, in: General Purpose Technologies and Economic Growth. MIT Press, pp. 85–120.

Hicks, J.R., 1935. Annual Survey of Economic Theory: The Theory of Monopoly. Econometrica 3, 1–20. doi:10.2307/1907343.

Hobijn, B., Şahin, A., 2009. Job-finding and separation rates in the OECD. Economics Letters 104, 107–111. doi:10.1016/j.econlet.2009.04.013.

Hopenhayn, H., Llobet, G., Mitchell, M., 2006. Rewarding Sequential Innovators: Prizes, Patents, and Buyouts. Journal of Political Economy 114, 1041–1068.

Hopenhayn, H.A., 1992. Entry, Exit, and firm Dynamics in Long Run Equilibrium. Econometrica 60, 1127–1150. doi:10.2307/2951541.

House, C.L., Shapiro, M.D., 2008. Temporary Investment Tax Incentives: Theory with Evidence from Bonus Depreciation. American Economic Review 98, 737–768.

Hummels, D., Klenow, P.J., 2005. The Variety and Quality of a Nation's Exports. American Economic Review 95, 704–723.

Impullitti, G., Licandro, O., 2018. Trade, Firm Selection and Innovation: The Competition Channel. The Economic Journal 128, 189–229. doi:10.1111/ecoj.12466.

Jaffe, A.B., 2000. The U.S. patent system in transition: Policy innovation and the innovation process. Research Policy 29, 531–557. doi:10.1016/S0048-7333(99)00088-8.

Kantenga, K., 2016. Sorting and Wage Inequality. Technical Report 660. Society for Economic Dynamics.

Karlis, D., 2003. An EM algorithm for multivariate Poisson distribution and related models. Journal of Applied Statistics 30, 63–77. doi:10.1080/0266476022000018510.

Keller, W., 2004. International Technology Diffusion. Journal of Economic Literature 42, 752–782. doi:10.1257/0022051042177685.

Khandelwal, A., 2010. The Long and Short (of) Quality Ladders. The Review of Economic Studies 77, 1450–1476.

Khandelwal, A., Topalova, P.B., 2011. Trade Liberalization and Firm Productivity: The Case of India. SSRN Scholarly Paper ID 1949292. Social Science Research Network. Rochester, NY.

Krugman, P., 1997. The Age of Diminished Expectations, Third Edition: U.S. Economic Policy in the 1990s. third edition ed., The MIT Press, Cambridge, Mass.

Lamadon, T., Manresa, E., Bonhomme, S., 2015. A Distributional Framework for Matched Employer Employee Data. Technical Report 1399. Society for Economic Dynamics.

Leibenstein, H., 1966. Allocative Efficiency vs. "X-Efficiency". The American Economic Review 56, 392–415.

Lentz, R., Piyapromdee, S., Robin, J.M., 2018. On Worker and Firm Heterogeneity in Wages and Employment Mobility; Evidence from Danish Register Data. PIER DISCUSSION PAPER 91.

Levinsohn, J., Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. The Review of Economic Studies 70, 317–341.

Loecker, J.D., Warzynski, F., 2012. Markups and Firm-Level Export Status. American Economic Review 102, 2437–2471.

Lucking, B., Bloom, N., Reenen, J.V., 2019. Have R&D Spillovers Declined in the 21st Century? Fiscal Studies 40, 561–590.

Magerman, T., Van Looy, B., Song, X., 2006. Data Production Methods for Harmonized Patent Statistics: Patentee Name Harmonization. SSRN Scholarly Paper ID 944470. Social Science Research Network. Rochester, NY.

Mayer, T., Melitz, M.J., Ottaviano, G.I.P., 2014. Market Size, Competition, and the Product Mix of Exporters. American Economic Review 104, 495–536. doi:10.1257/aer.104.2.495.

Melitz, M.J., 2003. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. Econometrica 71, 1695–1725.

Melitz, M.J., Redding, S.J., 2013. Firm Heterogeneity and Aggregate Welfare. SSRN Scholarly Paper ID 2244085. Social Science Research Network. Rochester, NY.

Mendes, R., van den Berg, G.J., Lindeboom, M., 2010. An empirical assessment of assortative matching in the labor market. Labour Economics 17, 919–929. doi:10.1016/j.labeco.2010.05.001.

Mion, G., Zhu, L., 2013. Import competition from and offshoring to China: A curse or blessing for firms? Journal of International Economics 89, 202–215. doi:10.1016/j.jinteco.2012.06.004.

Moreno-Centeno, E., Escobedo, A.R., 2016. Axiomatic aggregation of incomplete rankings. IIE Transactions 48, 475–488. doi:10.1080/0740817X.2015.1109737.

Moretti, E., 2019. The Effect of High-Tech Clusters on the Productivity of Top Inventors. Working Paper 26270. National Bureau of Economic Research. doi:10.3386/w26270.

Mortensen, D.T., Pissarides, C.A., 1994. Job Creation and Job Destruction in the Theory of Unemployment. The Review of Economic Studies 61, 397–415. doi:10.2307/2297896.

Mueller, S., 2008. Capital Stock Approximation using Firm Level Panel Data. Jahrbücher für Nationalökonomie und Statistik 228. doi:10.1515/jbnst-2008-0405.

Naidu, S., Posner, E.A., Weyl, G., 2018. Antitrust Remedies for Labor Market Power. Harvard Law Review , 536–601.

OECD, 2019. OECD iLibrary — Strictness of employment protection legislation: Regular employment. https://www.oecd-ilibrary.org/employment/data/employment-protection-legislation/strictness-of-employment-protection-legislation-regular-employment_data-00318-en.

Olley, G.S., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica 64, 1263–97.

Pearce, J., 2019a. Firm-Inventor Links and the Composition of Innovation. Working Paper , 31.

Pearce, J., 2019b. Idea Production and Team Structure. Working Paper , 84.

Peeters, B., Song, X., Caellert, J., Grouwels, J., Van Looy, B., 2010. Harmonizing harmonized patentee names: An exploratory assessment of top patentees. Eurostat Working Paper .

Peruzzi, M., Zachmann, G., Veugelers, R., 2014. Remerge: Regression Based Record Linkage With An Application To PATSTAT. Bruegel Working Paper 10.

Piazza, R., Zheng, Y., 2019. Innovate to Lead or Innovate to Prevail: When Do Monopolistic Rents Induce Growth? Working Paper 19/294. IMF.

Poege, F., Harhoff, D., Gaessler, F., Baruffaldi, S., 2019. Science quality and the value of inventions. Science Advances 5, eaay7323. doi:10.1126/sciadv.aay7323.

Pons, P., Latapy, M., 2005. Computing Communities in Large Networks Using Random Walks, in: Yolum, p., Güngör, T., Gürgen, F., Özturan, C. (Eds.), Computer and Information Sciences - ISCIS 2005, Springer Berlin Heidelberg. pp. 284–293.

Potterie, B.V.P.D.L., Lichtenberg, F., 2001. Does Foreign Direct Investment Transfer Technology Across Borders? The Review of Economics and Statistics 83, 490–497.

Rogerson, R., Shimer, R., Wright, R., 2005. Search-Theoretic Models of the Labor Market: A Survey. Journal of Economic Literature 43, 959–988. doi:`10.1257/002205105775362014`.

Romer, P.M., 1990. Endogenous Technological Change. Journal of Political Economy 98, S71–S102. doi:`10.1086/261725`.

Sakakibara, M., Branstetter, L., 2001. Do Stronger Patents Induce More Innovation? Evidence from the 1988 Japanese Patent Law Reforms. RAND Journal of Economics 32, 77–100.

Schott, P.K., 2004. Across-Product versus Within-Product Specialization in International Trade. The Quarterly Journal of Economics 119, 647–678.

Scotchmer, S., 1991. Standing on the Shoulders of Giants: Cumulative Research and the Patent Law. Journal of Economic Perspectives 5, 29–41.

Shu, P., Steinwender, C., 2018. The Impact of Trade Liberalization on Firm Productivity and Innovation. Innovation Policy and the Economy, Volume 19 , 39–68.

Silipo, D.B., 2005. The Evolution of Cooperation in Patent Races:Theory and Experimental Evidence. J Econ 85, 1–38. doi:`10.1007/s00712-005-0115-0`.

Stigler, G., 1976. The Xistence of X-Efficiency. American Economic Review 66, 213–16.

Syverson, C., 2017. Challenges to Mismeasurement Explanations for the US Productivity Slowdown. Journal of Economic Perspectives 31, 165–186. doi:`10.1257/jep.31.2.165`.

Tarullo, D.K., 2014. Longer-Term Challenges for the American Economy. Technical Report 801. Board of Governors of the Federal Reserve System (U.S.).

Thompson, N., Kuhn, J.M., 2017. Does Winning a Patent Race Lead to More Follow-On Innovation? SSRN Scholarly Paper ID 2899088. Social Science Research Network. Rochester, NY.

Trefler, D., 2004. The Long and Short of the Canada-U.S. Free Trade Agreement. The American Economic Review 94, 870–895.

van Ark, B., O'Mahoney, M., Timmer, M.P., 2008. The Productivity Gap between Europe and the United States: Trends and Causes. Journal of Economic Perspectives 22, 25–44. doi:10.1257/jep.22.1.25.

Wooldridge, J.M., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. Economics Letters 104, 112–114. doi:10.1016/j.econlet.2009.04.026.

Yoo, Y., Escobedo, A.R., Skolfield, J.K., 2019. A New Correlation Coefficient for Aggregating Non-strict and Incomplete Rankings. arXiv:1801.07793 [math, stat] , 1–48arXiv:1801.07793.

Zizzo, D.J., 2002. Racing with uncertainty: A patent race experiment. International Journal of Industrial Organization 20, 877–902. doi:10.1016/S0167-7187(01)00087-X.

Appendices

Appendix A

Summary Statistics for German Manufacturing Firms

Table A.1 displays summary statistics for our sample of firms entering our final estimation of the effect of import competition on within firm productivity.

Table A.1: Summary Statistics for Sample Firms

Variable	Mean (1)	SD (2)	P25 (3)	Median (4)	P75 (5)	Obs. (6)
Firm productivity	2.82	0.85	2.26	2.72	3.21	78,414
Deflated Revenue (1000 €)	97,600	1,21,000	5,443	14,200	44,200	78,414
Labor (FTEs)	351.10	2773.90	47	98	244	78,414
Deflated capital stock (1000 €)	61,000	613,000	2,662	8,220	28,200	78,414
Deflated intermediate inputs (1000 €)	70,700	973,000	3,088	8,734	28,800	78,414
Deflated capital per FTE (1000 €)	118.25	130.15	43.57	81.28	145.77	78,414
% of revenue from exports	23.86	25.16	0.54	16.46	40.31	78,414
Export status dummy	0.78	0.42	1	1	1	78,414
R&D status dummy	0.35	0.48	0	0	1	78,414
$\frac{p_f}{avg.p_g}$	3.19	11.40	0.90	1.26	2.23	78,414
Number of products	4.04	8.53	1	2	4	78,414
Total import competition	5.45	10.53	0.04	0.97	5.74	78,117
High-income import competition	1.70	4.20	0	0.15	1.42	78,117
Low-income import competition	3.75	9.02	0.02	0.40	2.97	78,117

Notes: Table A.1 reports summary statistics for sample firms. All statistics are based on the sample of firms entering the estimation. Since firms without contemporaneous import competition measures can enter the estimation, N is slightly lower for these variables.

Table A.2: Comparison of Firms with Competition from High vs. Low Income Countries

	Firms predominantly exposed to import competition from high-income countries (mean / median)	Firms predominantly exposed to import competition from low-/middle-income countries (mean / median)
$IC^{High-Income}$	13.44 / 10.63	1.29 / 0.63
$IC^{Low-Income}$	1.79 / 1.30	20.22 / 13.41
K/L (€/ fte)	123,185 / 83,251	92,076 / 68,846
R&D Ex / L (€/ fte)	5,926 / 1,683	1,340 / 0
R&D Ex / Sales (%)	3.05 / 1.06	0.76 / 0

Note: Firms are exposed predominantly to import competition from high-/low-income countries if competition from high-/low-income countries is at least three times larger than competition from low-/high-income countries. Import competition from high-income countries and from middle- and low-income countries as in equation (2.1), unweighted mean / median, 2000-2014. Import competition is the share (in domestic production of German manufacturing firms) of imports from a certain group of countries. The group of high-income countries (for $IC_{it-1}^{High-Income}$) includes USA, Canada, Japan, and South Korea. The group of low-income countries (for $IC_{it-1}^{Low-Income}$) includes China, India, Russia, Brazil, South Africa, Argentina, Chile, Mexico, Malaysia, Turkey, Thailand, Tunisia, Bangladesh, Indonesia, Philippines, Vietnam and Pakistan (see 2.2 for a discussion on country selection). Capital to labor ratio, K/L, is measured in euro per employee (in full time equivalents, fte), unweighted mean / median, 2000-2014. R&D Ex / L is R&D expenditures in euro per employee (in full time equivalents, fte), unweighted mean / median, 2000-2014. R&D Ex / Sales is R&D expenditures in euro over total sales in euro (in %), unweighted mean / median, 2000-2014.

Appendix B

Firm-Specific Price Indices

We construct a firm-specific price index to purge firm revenues from price variation. The calculation of this price index closely follows Eslava et al. (2004). In particular, we construct a firm-specific Tornqvist index for the firms' composite revenue from its various products:

$$P_{it} = \prod_{g=1}^{n} [\frac{p_{igt}}{p_{igt-1}}]^{\frac{1}{2}(s_{igt}+s_{igt-1})} P_{it-1} \tag{B.1}$$

where p_{igt} is the price of good g and s_{igt} is the corresponding share of this good in the production at firm i in period t. Thus, the growth of the index value is the product of the individual products' price growths, each weighted with the average revenue share of that product over this year and the last. We use the first year available in the data as our base year, i.e. we set $P_{t=2000} = 100$. For firms entering after 2000, we use an industry average of our firm price indices as a starting value. Similarly, we follow Eslava et al. (2004) and impute missing product price growth information in other cases with an average of product price changes within the same industry (for some products, firms do not have to report quantities, because they would not be meaningful).

Appendix C

Construction of Capital Stock from Investment

We construct capital stocks at the firm level using a perpetual inventory method. To estimate the first capital stock of every series, we combine information on the value of yearly depreciations of firms τ_{it} included in the AFiD-data, with information on the average lifetime of capital goods, $D_t(\Theta)$, where Θ=(equipment,buildings) highlights that this information exists separately for building and equipment capital (this information is provided by the Federal Statistical Office). For now, let us abstract from the different capital good types. Note that the lifetime of capital goods contains information about their real depreciation rate.[1] As is standard in the literature, we assume that capital depreciates at a constant rate and that it is fully destroyed (depreciated) at the end of its lifetime. Let us define the amount of capital which depreciated during the production process in industry j and period t as:

$$\phi_{jt} = \delta_{j0} K_{jt}$$

where $\delta_j 0$ is the depreciation rate of capital purchased at time $t = 0$. The average lifetime of a capital stock purchased in year $t = 0$ then equals:

$$D_{j0} = \frac{1}{K_{j0}} \sum_{0}^{\infty} \phi_{jt} t = \frac{1}{K_{j0}} \sum_{0}^{\infty} \delta_{j0} K_{jt} t \tag{C.1}$$

[1]Ultimately, we augment an approach based on Mueller (2008) by backing out the implied depreciation rate in a way that is consistent with a constant depreciation rate, the prevailing assumption in the literature.

With a little algebra, one can show that assuming a standard capital depreciation of the form $K_{jt} = K_{j0}(1-\delta_{j0})^t$, and substituting it into (C.1) gives:

$$D_{j0} = \frac{\delta_{j0}}{\ln(1-\delta_{j0})\ln(1-\delta_{j0})}$$

As $D_{jt}(\Theta)$ is known, we can recover δ_{jt} by solving this expression numerically for each year and each capital type, Θ=(equipment,buildings). This generates two depreciation rates for each point in time. We then define a single industry-specific depreciation rate by using the shares of the industry-wide stocks of equipment and building capital at time t as weights. Finally, we simplify by assuming that the depreciation rate for the entire capital stock in each period equals the depreciation rate of newly purchased capital, i.e. $\delta_{j0} = \delta_{jt}$. Having calculated δ_{jt}, we can recover a starting capital stock for every firm by using information on the value of yearly deprecations, $DEPR_{it}$, from the AFiD-database:

$$K_{it} = \frac{DEPR_{it})}{\delta_{jt}}$$

Now we can compute our capital series by:

$$K_{it} = K_{it-1}(1-\delta_{jt-1}) + I_{it-1}.$$

where I_{it} denotes firm-specific investment. As our capital stocks are based on information on the lifetime of capital goods, they are a closer approximation of the capital actually used in firms' production activities than capital stocks based on book values. This is because firms might buy and sell their capital goods not to market prices and have incentives to depreciate their accounting capital excessively (House and Shapiro, 2008).

Appendix D

First Stage Regressions: Predicting German Competition with Competition Abroad

In the following we present the first stage regressions belonging to our baseline results presented in the main text. As we always use the same instruments for the same endogenous variables, our first stage regressions are identical for all regressions using the same set of firms. Hence, we only show two sets of first stage regressions: one for the full sample firms and one for the sample of firms engaging in R&D activities. Those first stage regressions are respectively reported in the following D.1 and D.2.

Table D.1: First Stage Regression Results
Full Sample

	$IMP_{it-1}^{High+Low}$ (1)	IMP_{it-1}^{High} (2)	IMP_{it-1}^{Low} (3)
$IS_{it-1}^{High+Low\rightarrow third}$	0.235***	-	-
	(0.0197)	-	-
$IS_{it-1}^{High\rightarrow third}$	-	-0.0995***	0.0314***
	-	(0.0117)	(0.0111)
$IS_{it-1}^{Low\rightarrow third}$	-	0.0156***	0.279***
	-	(0.0051)	(0.0224)
Firm x Industry FE	YES	YES	YES
Time FE	YES	YES	YES
Firm-level controls	YES	YES	YES
Observations	78,414	78,414	78,414
R-squared	0.950	0.927	0.946
Number of firms	16,925	16,925	16,925

Notes: This table reports results from the first stage regressions when estimating equation (2.10) by IV using the full sample of firms. The dependent variable in columns 1, 2, and 3 respectively is the lagged total import competition measure, the lagged high-income import competition measure, and the lagged low-income import competition measure. All regressions include time and industry times firm fixed effects and controls for firms' number of products and export intensity. Standard errors are clustered at the firm-level. Significance: *10 percent, **5 percent, ***1 percent.

Table D.2: First Stage Regression Results Only R&D-Firms

	IMP_{it-1}^{High}	IMP_{it-1}^{Low}
	(1)	(2)
$IS_{it-1}^{High \rightarrow third}$	0.118***	0.0210
	(0.0205)	(0.0176)
$IS_{it-1}^{Low \rightarrow third}$	0.0308***	0.228***
	(0.0109)	(0.0299)
Firm x Industry	FE	YES
Time FE	FE	YES
Firm-level controls	FE	YES
Observations	26,544	26,544
R-squared	0.928	0.952
Number of firms	5305	5305

Notes: This table reports results from the first stage regressions when estimating equation (2.10) by IV using the sample of firms that engage in R&D activities. The dependent variable in columns 1 and 2 respectively is the lagged high-income import competition measure and the lagged low-income import competition measure. All regressions include time and industry times firm fixed effects and controls for firms' number of products and export intensity. Standard errors are clustered at the firm-level. Significance: *10 percent, **5 percent, ***1 percent.

Appendix E

Using Patent Data as an Employer-Employee Data Set

Since PATSTAT does not contain IDs, only string names, I consolidate spelling mistakes and disambiguate entities with the same name before using the data. This appendix describes the procedure.

First, Magerman et al. (2006) have already constructed consolidated identifiers by correcting spelling mistakes, omitting titles and reading out abbreviations like "Ltd.". They have also constructed a sector variable, which assigns names in the database to categories like "company", "individual", "university" etc. After fusing such different spellings of the same name, they find an additional 30% of patents for the top 450 applicants, compared to the raw HAN identifiers provided by PATSTAT.

Second, Peeters et al. (2010) have manually checked the record of the top 450 applicants and searched for additional possible variants in the data. They can assign another 30% of patents to these applicants. However, since some of these applicants have over 100.000 patents in different countries, different spellings and mistakes play a much larger role than in the general population.

To disambiguate additional names both on the inventor and firm side, I clean names similarly to Magerman et al. (2006) and then sort all words alphabetically. This equates reversed spellings of names like "Erik van Houten" and "van Houten, Erik". This reduces the number of unique inventor identifiers by another 25%.

I additionally clean firm names of addresses that are sporadically entered in the field "name", e.g. "Intel Corporation, Santa Clara, CA". This fuses around 3% of the remaining firm identifiers.

To gauge the quality of the resulting ID, I draw a list of prominent inventors from Wikipedia and link them to our data. Just as Peeters et al. (2010) for the firm side, I find that these highly active individuals are split over multiple IDs due to spelling mistakes, different name formats etc. However, the automated correction of Magerman et al. (2006) already does a decent job of aggregating them: After manual search, I e.g. link 38 PATSTAT person IDs to the most prolific inventor in the world (Dr. Shunpai Yamazaki). Magerman et al. (2006) already linked the most important 30, so I can only marginally improve upon their results. My 38 IDs participate in 5585 patent families across the world while the 30 IDs of Magerman et al. (2006) participate in 5581. The newly discovered name variants are clearly errors that only show up once. In addition, such spelling variants often show up within a patent family where the inventor is also cited on other patents. The patent family is the relevant unit of observation. Thus, even if undetected spelling variants exist, they are largely irrelevant to my productivity measures. I thus have confidence that the IDs provided by Magerman et al. (2006) capture the large majority of an inventor's patents.

However, this still leaves the problem that some names might belong to more than one inventor. Combining such inventors into one person would create the impression of a prolific inventor frequently moving between firms.

First, I collect the frequency with which words occur in the inventor names submitted on patents in each country. I then eliminate inventor names that do not contain two infrequent words: E.g., "Erik van Houten" contains two words common in Dutch names ("Erik" and "van") and only one uncommon word "Houten". Thus, I will not consider this inventor in the sample.

Second, PATSTAT contains the IPC classes associated with each inventor's patents. Inventors will typically not master a variety of technical fields and thus names with more diverse portfolios are more likely to stand for more than one inventor. Specifically, I exclude workers whose most common IPC 4-digit category accounts for 20% or less of their patents, whose top technology field accounts for 50% or less of their patents and whose top two technology fields account for 80% or less of their patents. I check these numbers against the statistics for inventors crosschecked with Wikipedia to guarantee that these criteria are not too strict.

Third, I exclude inventors from the sample who were active for more than 40 years, on the basis that these are likely overlapping inventors of the same name.

The observed time span, the diversity of IPC classes and technology communities and the number of distinct names are conceptually different criteria. Nonetheless, they are reasonably correlated (0.15-0.6), which suggests that the criteria identify suspect inventors reliably.

Appendix F

Constructing Technology Clusters from IPC Classes

This appendix details how I extract sub-labor markets from the IPC classes of inventors' patents. Each patent is assigned to one or more IPC classes that describe its technological contents. Not all inventors are interchangeable. Not all inventors can work on all research projects. I.e., there is horizontal as well as vertical differentiation between inventors. To sort all inventors into one ranking would thus be misguided. The goal of the algorithm below is to separate inventors into groups: These groups have to be so small that every inventor in the group can contribute to the work of the other members of the group. However, they have to be so large as to include every inventor who could substitute for the members of the group.

I reduce the sample to all patents with only one inventor, so that the assignation of IPC classes to inventors is unambiguous. I observe the succession of combinations of IPC 4-digit classes every inventor patents in, sorting IPC classes from the same patent or from patents in the same year in a random order. From this I compute the conditional probability of an inventor whose last patent was in one combination to move to another one. E.g.: If only one inventor ever applies for a patent with the IPC class "A01P" and then patents in the class "B06P", I would conclude that the two combinations are very similar, since 100% of inventors moved from one to the other.

I find that even IPC 8-digit classes form a network that is only sparsely connected by moving inventors: Most inventors only patent in very few classes and mobility between classes is rare.

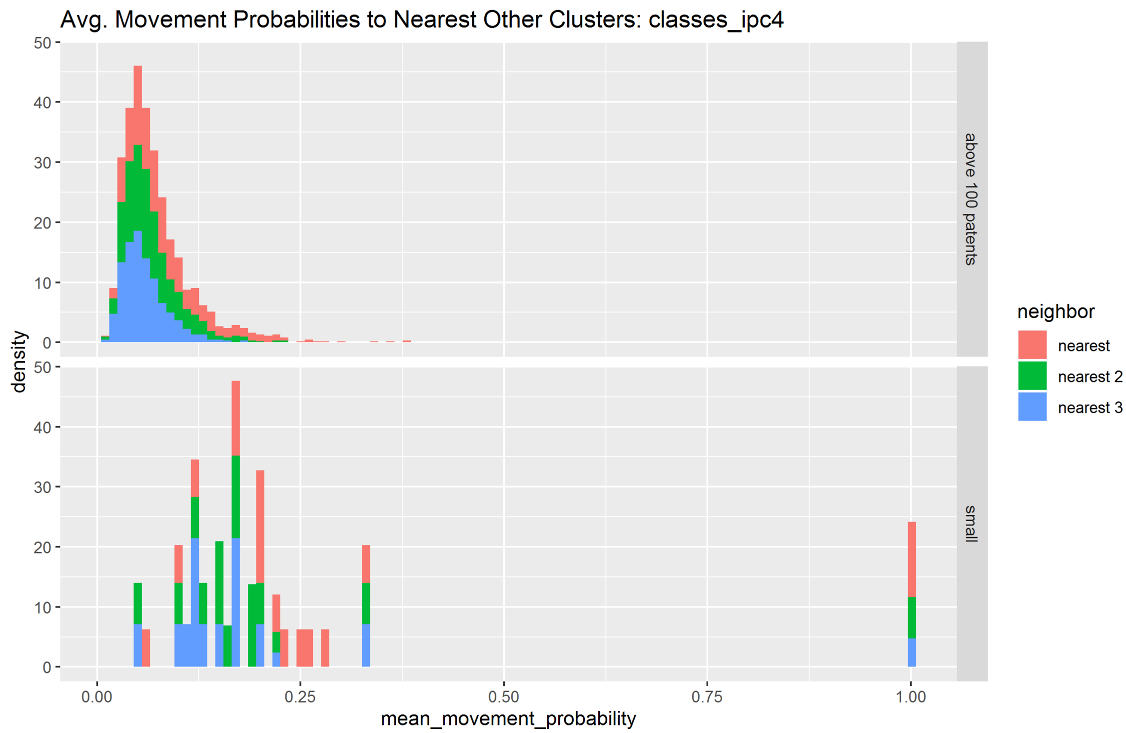

Figure F.1: The figure shows the distribution of movement probabilities between IPC class combinations. The top figure shows the distribution for common IPC classes (with more than 100 patents). The bottom figure shows the same distribution for the less common classes. Evidently, less frequent classes are often strongly connected. In contrast, the frequent classes stand more alone. Red, green and blue describe the movement probabilities to the nearest, nearest two and nearest three other classes.

This sparseness of the network also determines my strategy for defining clusters: Since the network has many nodes, few strong edges and the number of final clusters and their geometrical forms are unknown, density based clustering will efficiently yield the network structure.

First, I assign every IPC class with less than 1% of patents to the nearest class with more than 1%, to avoid many small clusters with few inventors. I then use density clustering among the large IPC classes to determine which classes to combine into clusters. The "knee" in the 3-nearest neighbor cdf is at roughly

0.11, which I take as the ϵ for density based clustering: All connections with a movement probability of 11% or higher are selected into the same cluster.

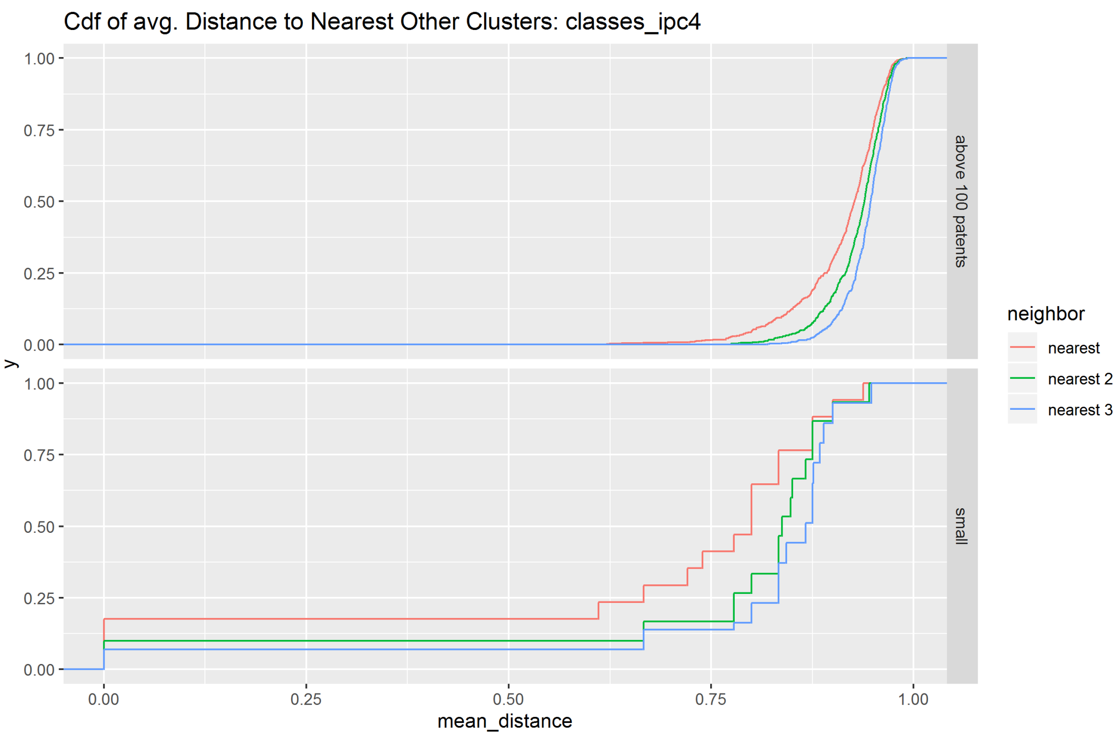

Figure F.2: knn distance plot of inventor movement probabilities. Distance is defined as 1- movement probability. Note the uptake of the cdf for big clusters at roughly 0.11. I will take this as the ϵ parameter in density based clustering. Thus, most small IPC class combinations will be fused into clusters.

The result of this procedure is a stable assignment of IPC classes to technology clusters. Around 20% of patents are part of the largest cluster. Figure F.3 shows the technology field assignment of the biggest IPC groups and the strength of their relations with each other. For comparison, figure F.4 also reports the community assignments of an alternative community finding algorithm for large data sets (Pons and Latapy, 2005). It results in significantly larger communities because small nodes with connections to two large communities often are enough to connect the two large communities. This happens even though these small notes represent a negligible amount of patents. Hence, the algorithm is highly sensible to which small nodes and weak edges are considered. If neither are included, the largest community contains roughly 50% of all patents, which is not plausible as a sub-labor market: Mobility within this large community is low.

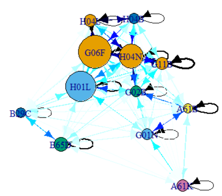

Figure F.3: Technology fields of and connections between the largest IPC classes. Classes were grouped into fields using a density based algorithm that groups together all classes connected through an inventor movement probability above 11%. Thicker and darker arrows denote more movements of inventors from one technology class to the other. The size of the classes denotes the number of patents assigned to each class.

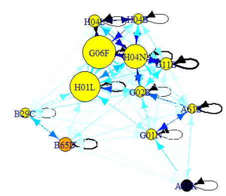

Figure F.4: Technology fields of and connections between the largest IPC classes. Classes were grouped into fields using the walktrap algorithm of Pons and Latapy (2005). Thicker and darker arrows denote more movements of inventors from one technology class to the other. The size of the classes denotes the number of patents assigned to each class.

Appendix G

Truncation Correction

In this framework, the expected number of patents per year λ_x^y is constant within one match. Specifically, I treat λ_x^y as the Poisson arrival rate of new patents, given x and y. Each match exists for a given number of years (l_{true}). Let type j denote all employment spells with the same l_{true} and λ_{true}. I understand the untruncated data as generated by a mixture distribution of different types of employment spells. I define $s_{l;\lambda}$ as the share of type $l;\lambda$ in the overall mix of types. E.g., all employment spells lasting 5 years and producing 0.3 patents per year would be considered a type, with $s_{5;0.3}$ giving the share of such employment spells in all spells.

$\boldsymbol{s}$, the vector of the individual type's population shares, has to be recovered from the observed minimum length of employment spells l_{ob} (the time between the first and the last patent) and the distribution of patents during these years. The only additional assumption necessary is that workers do not leave a firm between two observed patents, so that I can recover a minimum length of each spell from the data. I will recover $\hat{\boldsymbol{s}}$ and from this construct unbiased estimates $\hat{\lambda}_x^y$ and $\hat{l}_x^y$ for each observation from the estimated distribution of true types.

This procedure is necessary since the estimates $\hat{\lambda}_x^y$ and $\hat{l}$ given P_{ob} & l_{ob} cannot be computed for each match in isolation: Consider a match for which I observe one patent in one year. This observation could either be an unproductive match that lasted for a long time or a productive, but short lived one. The one data point itself is not informative on the matter. However, if unproductive and long matches were common in the data, I would also observe some of them. Thus, the whole observed distribution informs my estimate for one specific observation.

Therefore, it is necessary to analyze the whole distribution jointly.
Given that the above setup already assumes a Poisson distribution for patents, a maximum likelihood estimator does not require additional assumptions, but is more efficient. Unfortunately, it requires the optimization of a non-linear log likelihood function over several 1000 parameters, so it is only feasible when making additional simplifying assumptions. Therefore, I estimate the spell distribution using GMM.
Given the above mixture distribution

$$N_{ob} = \sum_{j}^{J} p(ob|j) * N(j) \tag{G.1}$$

N_{ob} denotes the expected number of times a specific outcome (like 2 patents interrupted by a year of inactivity) is observed. It equals the sum of the expected number of occurrences given each of the specific types. $p(ob|j)$ is a constant number: E.g. the chance to observe the above two patents interrupted by one year of silence for type $5; 0.3$ is about 2%. Treating $N(j)$ as the coefficients to be estimated, one has a data set with several million different possible outcomes and how often they have occured in the data, which one can use to estimate the several thousand $N(j)$s. Note that since $N(j)$ has to be greater than 0, this is not strictly linear. However, it is still computable in a very reasonable time frame:
Because of the positivity constraint on all coefficients, there is no analytical solution and several possible numerical techniques exist. Aside from estimating the whole system of equations jointly, splitting the data is a possibility, too: Since observations with e.g. 20 observed years can only be created by spells of at least length 20, one could estimate longer employment lengths first and then "cascade" down the spell lengths. Additionally, it is numerically hard to recover the distribution for very short spells because there are comparatively few different observable outcomes. I test specifications where I restrict the underlying true employment spells to be either at least 2 or at least 4 years long. I either use the whole distribution in the estimation (including the very short outcomes), or exclude the shortest observed outcomes from the estimation as well. This leads to 8 different numerical techniques.
Since their qualitative results are very similar and additional assumptions do not seem to yield more stable results, I opt to estimate using all available data and as-

suming that no employment spell is shorter than 4 years. While this method leads to a slightly better fit, all different strategies yield very comparable estimates:

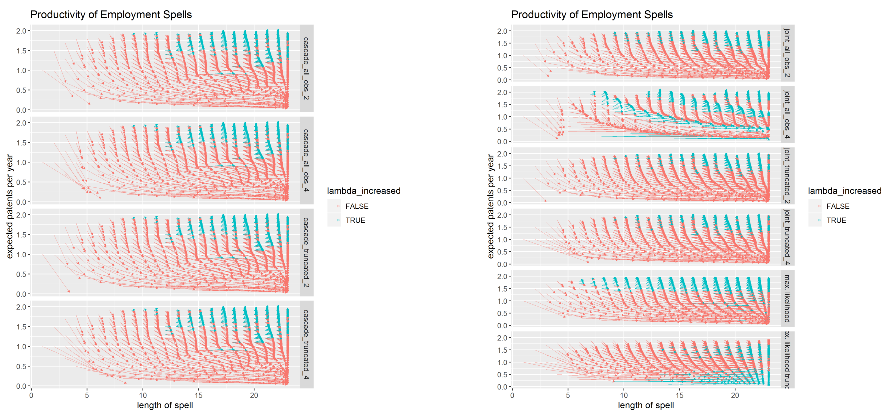

Figure G.1: Adjustment of observed employment spell productivity and length. The starting point of each arrow is the productivity and length observed in the data without the correction routine. The end point of each arrow gives the new estimated arrival rate of patents after the routine has concluded. Red highlights spells where the observed productivity was adjusted downward, blue highlights spells where the observed productivity was adjusted upwards. Each panel is the result of a slightly different numerical technique. The left table contains results when imputing for each spell length separately, the right table contains the results when fitting to the whole data at once. Within each table, the top two panels report the result when assuming that employment spells last at least 4 or 2 years respectively. The lower two panels report results when making the same assumption, but also only targeting the part of the data that contains at least 4 or 2 consecutive years. All methods come to broadly similar conclusions. Estimating for each spell length separately is less efficient, but much faster.

The Poisson distribution underlies all of the above estimations. This distribution is used both in theoretical models (Akcigit and Kerr, 2018) and in empirical applications throughout a vast range of scenarios, even including sport scores (Karlis, 2003). The central assumption of the Poisson distribution is that the arrival rate of events is constant, which seems suspect in many circumstances including patents: It seems reasonable that after a successfully completed project, the arrival rate of success falls and then rises again after some time has passed. However, in practice, it seems that inventors work on different projects simultaneously so that a constant arrival rate is a good fit for the data. The only systematic forecasting error of the Poisson model is for very successful spells:

The model assumes that inventors with multiple patents per year can uphold their performance, which seems to not always be the case. However, this concerns a negligible number of inventors. G.2 reports systematic mismatch of the Poisson model of patent invention for each numerical technique. Evidently, the fit is very good for all outcomes except rare and high productivity outcomes.

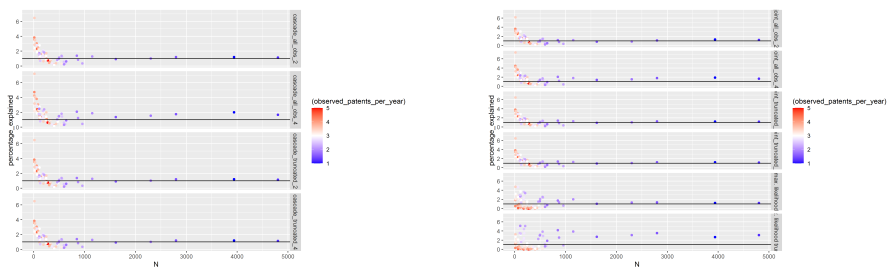

Figure G.2: The ratio of the predicted times each outcome should occur and the actual number of occurrences. The fit is very good for results occurring more often, there is a slight upward bias for very rare and very productive spells, whose frequency of occurrences is overestimated. Each panel is the result of a slightly different numerical technique. The left table contains results when imputing for each spell length separately, the right table contains the results when fitting to the whole data at once. Within each table, the top two panels report the result when assuming that employment spells last at least 4 or 2 years respectively. The lower two panels report results when making the same assumption, but also only targeting the part of the data that contains at least 4 or 2 consecutive years. All methods come to broadly similar conclusions. Estimating for each spell length separately is less efficient, but much faster.

Once I have estimated a distribution of λ_i^f and (l) with either GMM or ML, I compute the implied shares of all types, given any realization of P_{ob} & l_{ob}. I can thus derive my final estimates $\hat{p}$ & $\hat{l}$ for any observation. Based on the same technique, I can also obtain an estimate of how likely it is to observe the underlying spell at all.

Appendix H

Simulation: Description and Results

While the Hagedorn et al. (2017) method is a consistent estimator, its performance in the actual data is more unclear: Since there are usually only a few observations for every inventor, a consistent estimator might not perform well in practice. A Monte Carlo simulation will reveal the estimator's performance in more realistic samples.

The simulated data covers a 40 year stretch of a technology cluster, just like the actual data. Every year, inventors enter the technology cluster. However, not all matches produce a patent and thus not all matches are observed. With around 50.000 observed inventors the simulated data is as large as the smallest actual technology cluster.

Inventors have a constant chance ρ to match with a firm. They then compare the firm's quality to the quality of their current firms and decide whether to switch or not. Whenever inventors have to decide between two firms, they will pick the one with the higher quality: Since the higher quality firm will produce more patents, it can offer a higher wage and secure the inventor.

In the main specification, the parameters of the model are as follows:

- The patent invention function is $\lambda_{x_i,y_f} = x_i * y_f$

- Inventors match with a new random firm with a 5% probability every year

- Inventors leave the economy with a 10% probability every year

- Inventors and firms will reject any matches that do not at least produce $\frac{skill^2+quality^2}{2.05}$

The algorithm to recover the estimates contains four steps:
First, using the estimated overall distribution of employment spells (appendix G), the algorithm computes the unconditional distribution of potential types for every observed spell: It computes that e.g. 5% of all observed spells with one patent are produced by employment spells with a patent arrival rate of 0.5 and a length of 7.
Second, using this underlying distribution, the algorithm draws 20 potential underlying productivities for every observed spell. These serve as hypotheses about the actual "true" productivity that led to the observed patent outcome.
Third, the algorithm prunes these hypotheses: It computes how many observed spells of a certain type we expect to see, given the drawn productivities. In the case of a firm with 100 employees, all of which have only one patent, it would e.g. conclude that a patent arrival rate of 0.5 and a length of 7 is an unreasonable hypothesis for these spells: The firm would also have to have more successful inventors. The "only one patent"-outcome is overrepresented in the data. The algorithm sequentially prunes these hypotheses, recomputing the expected distribution after each discarded draw. The algorithm stops after only 5 hypotheses are remaining.
Lastly, the algorithm runs the whole ranking estimator five times, once for each set of drawn productivities. This allows to estimate how sensitive an estimated rank is to plausible variations in productivities and thus how large the estimation error for each ranking is.

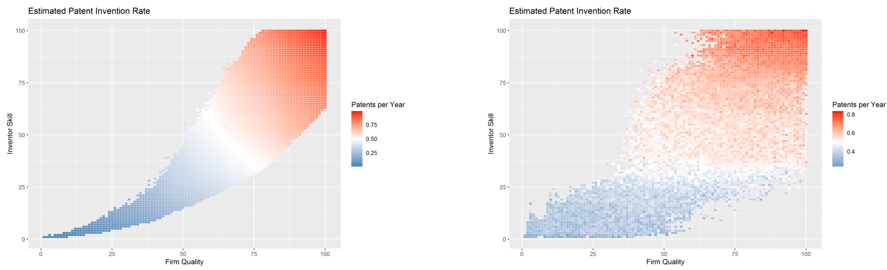

Figure H.1: The left graph reports the patent invention function using the true parameters of the model: Combinations of inventors and firms with higher skill produce more patents according to $\lambda_{x_i,y_f} = x_i * y_f$. Grey areas of the matching plane have no matches in them, so the patent arrival rate is not reported for these.

Just using global rankings, the estimator recovers these parameters reliably: Figure H.1 compares the estimated and the true production function, which are by and large identical. Figure H.2 shows the number of matches for each skill and quality level. The estimator also recovers the core region with match support reliably. Only some single matches are estimated to be in actually empty regions of the matching plane.

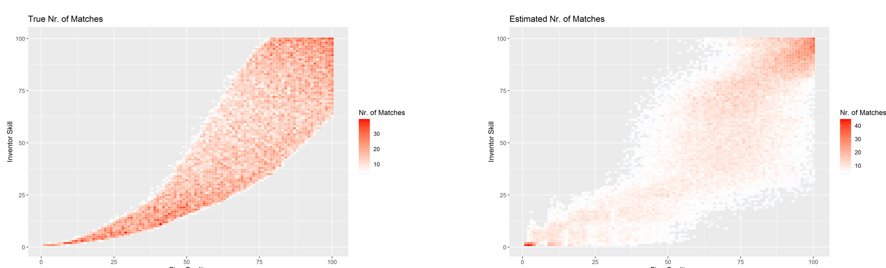

Figure H.2: The left graph shows the matching behavior of inventors and firms, using their true skill and quality bins. The grey area has no matches, because inventors and firms reject matches that do not produce a positive matching surplus. The right panel shows the estimated distribution of matches. Apart from some single matches in the empty regions, the estimate recovers the true distribution well.

Appendix I

Numerical Simulation of the Model Economy

This appendix details the result of a simulation of the model economy where Λ^{dis} is much higher than the sum of the interest rate r and the separation rate δ. For this purpose, $\Lambda^{dis}(0)$ is set to 50%, the interest rate to 5% and the separation rate to 5%. 50% is clearly to high for the rate of disruptive technology change, as it would imply that every second sector of the economy is disrupted every year, making incremental inventors obsolete. Nonetheless, even under these extreme conditions, the qualitative results of the model hold:

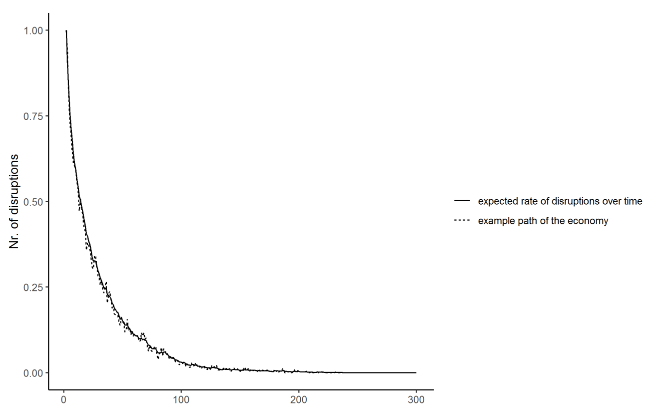

Figure I.1: The graph shows the average rate of disruptive inventions throughout the whole economy for $\delta = r = 0.05; \Lambda^{dis}(0) = 0.5$.

While the economy converges to the non-disruptive equilibrium much slower (100 is the simulated time in the main paper), the qualitative path is very similar to that of the economy where the parameter restriction holds.

A closer look at the expected change in the disruptive rate makes clear why this is the case (figure I.2): Even with these extreme assumptions, the expected change in the rate of disruption is only positive when the risk of a disruptive invention in the technology field is already very low, only to converge to 0 from above.

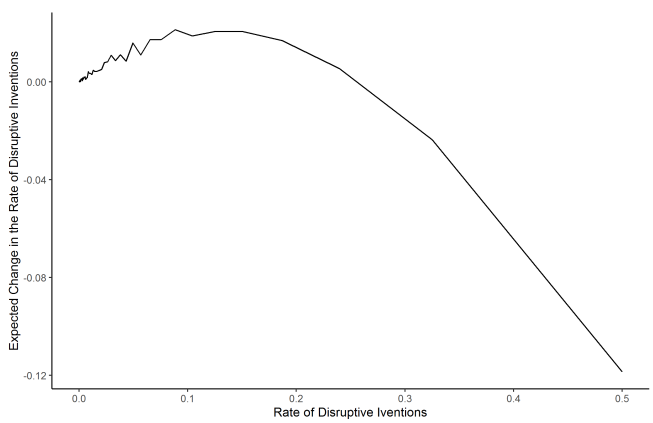

Figure I.2: The expected change in the arrival rate of disruptive inventions for a sector. The rate is expected to go down when it is high and to slightly increase when it is already very low. However, if no disruption happen, the expected change approaches 0 as the rate of disruption becomes zero itself.

Clearly, an equilibrium where technology fields with increasing and decreasing rates of disruption cancel each other out in the aggregate is not achievable for all plausible values of $\Lambda^{dis}(0)$.

Appendix J

Abbreviations

AFiD	Amtliche Firmendaten in Deutschland: Firm panel of the German statistical Offices
AMADEUS	Firm panel compiled by the Bureau van Dijk
CDF	Cumulative Distribution Function
EPO	European Patent Office
FDI	Foreign Direct Investment
FE	Fixed Effects
FTE	Full Time Equivalent
GML	Generalized Maximum Likelihood
GMM	Generalized Method of Moments
ICT	Information and Communication Technology
IO	Industrial Organization
IPC	International Patent Classification: System of codes that designate the technology areas of patent applications
IT	Information Technology
IV	Instrumental Variable

knn k-nearest-neighbors

ML Maximum Likelihood

M and A Mergers and Aquisitions

NP-hard non-deterministic polynomial-time hard: A problem that cannot be solved in polynomial time

NUTS Nomenclature des Unités Territoriales Statistiques: internationally standardized subdivisions of countries

OLS Ordinary Least Squares

PATSTAT Global patent data set compiled by the European Patent Office

PRODCOM Products of the European Community: 8-digit product codes of the European Union

R and D Research and Development

TFP Total Factor Productivity: Productivity residual of a multifactor production function

TFPQ Total Factor Productivity, Quantity based: Productivity residual of a multifactor quantity production function

TFPR Total Factor Productivity, Revenue based: Productivity residual of a multifactor revenue production function