Industry and Productivity Dynamics in Germany

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Unternehmens- und Produktivitätsdynamik in Deutschland

Der Rückgang des Produktivitätswachstums in den letzten Jahren sowie die nachlassende Unternehmensdynamik in zahlreichen Industrieländern stehen ganz oben auf der politischen Agenda vieler Entscheidungsträger, die langfristige Auswirkungen auf Wirtschaftswachstum und Beschäftigung befürchten. Die Kohärenz dieser Phänomene legt einen Zusammenhang nahe, dessen empirische Bewertung für wirtschaftspolitische Maßnahmen eine entscheidende Stütze bietet. Dieses Projekt leistet einen Beitrag zu dieser Debatte und untersucht die Entwicklung und den Zusammenhang zwischen Industriedynamik und Produktivitätsentwicklung in Deutschland.

In den letzten Jahrzehnten hat die Bundesregierung eine Vielzahl politischer Initiativen eingeführt, welche auf die Reduzierung von Markteintrittsbarrieren abzielen; darunter die etablierten EXIST-Gründerstipendien und das ERP-Gründerdarlehen der KfW, aber auch das INVEST-Programm und das Green Startup-Programm. Diese Programme senken die Opportunitätskosten von Unternehmensgründungen, erleichtern den Markteintritt und schaffen Innovationsanreize für Gründungen, indem der Zugang zu Kapital und branchenspezifischem Wissen vereinfacht wird.

Darüber hinaus hat sich die politische Debatte nicht nur zur Förderung des Markteintritts, sondern auch zur Erleichterung des Marktaustritts zugespitzt. Die Schließung von Unternehmen rückte zunehmend in den Fokus der politischen Entscheidungsträger, da die Angst vor einer Fehlallokation von Ressourcen und einer potenziellen "Zombifizierung" (McGowen et al., 2017) zahlreicher Volkswirtschaften zunahm. Bereits vor dieser Debatte zielten politische Maßnahmen wie die deutsche Insolvenzreform von 1999 darauf ab, ineffizienten und verschuldeten Unternehmen den Ausstieg zu erleichtern, indem sie eine strengere Insolvenzanmeldepflicht und eine breitere Definition von Insolvenz und Verschuldung einführten.

Obwohl die Wirksamkeit solcher Programme zur Förderung der Unternehmensdynamik seit ihrer Einführung in den 1980er Jahren diskutiert wird, spielen die direkten Auswirkungen von Markteintritten und -austritten auf die Leistungsfähigkeit und Produktivität etablierter Unternehmen bisher eine untergeordnete Rolle. Ob die angestrebte Steigerung der Unternehmensdynamik tatsächlich zu einer Steigerung der Gesamtproduktivität führt, sollte jedoch ein zentrales Kriterium dieser Maßnahmen sein.

Die Analyse dieses Projekts zeigt eine abnehmende Unternehmensdynamik in fast allen Regionen und Branchen mit der Ausnahme des IT-Sektors und der Region Berlin. Bis 2011 war die Eintrittsrate über alle Branchen hinweg höher als die Austrittsrate. Zwischen 2011 und 2015 hat sich dieses Verhältnis umgekehrt, so dass mehr Unternehmen aus dem Markt ausgeschieden als eingetreten sind. Seit 2015 ist die Eintrittsrate wieder höher als die Austrittsrate.

Das aggregierte Produktivitätswachstum ist über den gesamten Beobachtungszeitraum hinweg positiv, verlangsamt sich jedoch im Laufe der Zeit deutlich. Etablierte Unternehmen leisten einen höheren Beitrag zum aggregierten Arbeitsproduktivitätswachstum im Vergleich zu Neueinsteigern und Aussteigern, wobei etablierte Unternehmen hauptsächlich durch innerbetriebliche Produktivitätssteigerungen im Zusammenhang mit Lerneffekten beitragen. Des Weiteren besteht ein erhebliches Maß an allokativer Ineffizienz, bei der sich Arbeitsanteile von produktiveren zu weniger produktiven Unternehmen verschieben; dies verhindert ein höheres Produktivitätswachstum.

Die Ergebnisse dieses Berichts deuten darauf hin, dass die zunehmende Förderung der Unternehmensdynamik dazu beitragen könnte, die bisher schwache Produktivitätsentwicklung anzukurbeln. Die empirische Evidenz wirft jedoch die Frage auf, ob sich die Entrepreneurship-Politik in den letzten Jahren zu sehr auf Hightech-Sektoren konzentriert hat. In Anlehnung an die Argumentation von Jorgenson et al. (2008) deuten die vorliegenden Ergebnisse darauf hin, dass Lowtech-Branchen als wichtige Treiber der Produktivitätsentwicklung agieren. Die gesamte Unternehmensturbulenz ist der Haupttreiber der Produktivitätsentwicklung in Lowtech-Sektoren und übersteigt den Effekt des bloßen Austauschs von Firmen deutlich: Ein Zusammenhang, der für Hightech-Sektoren in dieser Form nicht besteht. Lowtech-Firmen konkurrieren, indem sie Technologien anpassen, während sie weniger in der Lage sind, die Konkurrenz mit IP oder F&E-Kapazitäten abzuwehren.

Jorgenson et al. (2008) vermuten, dass diese Technologieadaption ein Treiber des Wettbewerbs und damit des Produktivitätswachstums darstellt. Um die industrielle Dynamik zu fördern, sollten politische Entscheidungsträger ihren Fokus auch auf Low-Tech-Firmen ausweiten. Jorgenson et al. (2008) zeigen in ihrer Analyse, dass die Diffusion von Informationstechnologien einer der Haupttreiber des US-Produktivitätswachstums in den 1990er Jahren war. Heute stellen die Digitalisierung und die Dekarbonisierung ähnliche technologische Herausforderungen dar. Obwohl die Grenze dieser Technologien noch nicht erreicht ist, wird die Ermöglichung der branchenübergreifenden und brancheninternen Adaption und Diffusion potenziell ebenso wichtig für die Förderung der Unternehmensdynamik und des Produktivitätswachstums sein wie die Entwicklung neuer Technologien.

Der von Jorgenson et al. (2008) aufgezeigte Mechanismus wirft ein Licht auf die Herausforderungen für den Unternehmensumsatz während und nach den Strukturkrisen, welche durch die Corona-Pandemie verursacht wurden. Während der ersten Phase verlangsamte die massive staatliche Unterstützung den Ausstieg von Unternehmen mit nicht lebensfähigen Geschäftsmodellen. Solche Unternehmen verbrauchten weiterhin Ressourcen, was dazu führte, dass wertvolle Ressourcen in ineffizienten Geschäftsmodellen zurück blieben. Darüber hinaus konnten solche Geschäftsmodelle mit Hilfe staatlicher Unterstützung konkurrieren, während junge Unternehmen nur begrenzte Unterstützung von der Regierungen erhielten. Dies führt zu einer geringeren industriellen Dynamik. Eine wichtige Herausforderung für die Zeit nach der Pandemie ist die Wiederbelebung der Eintrittsraten, die Stimulierung der Technologieadaption und die Übernahme neuer Geschäftsmodelle als Grundlage für die Wiederherstellung oder sogar Steigerung des Produktivitätswachstums über das Niveau vor der Krise hinaus.

Industry and Productivity Dynamics in Germany

The decline in productivity growth over the last ten years as well as decreasing business dynamics in many industrialized countries are on top of the political agenda of many decision makers, fearing long-term impact on economic growth and employment. The coherence of these phenomena suggests a relationship between both, which calls for empirical evaluation on which economic policy can base decisions on. In this project we contribute to this debate and empirically investigate the evolution and relationship between industry dynamics and productivity development in Germany.

Over the last decades, the German government introduced a variety of political initiatives that aim at the reduction of barriers to market entry, including the established EXIST startup scholarships and the ERP startup loan from KfW, but also the INVEST Program and, more recently, the Green Startup Program. These programs aim at reducing the opportunity costs of starting businesses, facilitating market entry and ultimately providing innovation incentives for entrants by simplifying access to capital and industry-specific knowledge.

In recent years, the policy debate not only on fostering market entry but also facilitating market exit became more pronounced. Business closure has increasingly become the focus of policymakers as fears of misallocation of resources and potential "zombification" (McGowen et al., 2017) of many economies have grown. Even before this debate, policies such as the 1999 German insolvency reform targeted at facilitating the exit of inefficient and indebted firms by introducing stricter insolvency filing requirements and broader definitions of insolvency and indebtedness.

Although the effectiveness of such programs in promoting business dynamics has been debated since their introduction in the 1980s, the direct effects of entry and exit on the performance and productivity of incumbent firms have so far played a minor role in the evaluation of policy measures. However, whether the intended increase in business dynamics actually leads to an increase in overall productivity should be a central criterion of these measures.

Our analysis shows declining business dynamics in almost all regions and sectors with the notable exception of the IT-sector and the region of Berlin. Until 2011, the entry rate across industries was higher than the exit rate. Between 2011 and 2015, this relationship has reversed, such that more firms exited the market than entered. From 2015 on, we observe a stronger entry than exit rate again.

Aggregate productivity growth is positive over the entire observation period, but slows down considerably over time. Furthermore, we measure a higher contribution to aggregate labour productivity growth of incumbents compared to entrants and exitors, where incumbents contribute most through within-firm productivity improvements related to learning effects. We also measure a substantial degree of allocative inefficiency, where labour shares shift from more to less productive firms, which hampers higher productivity growth.

Our results suggest that finding ways to foster business dynamics will likely help to mitigate the weak productivity development. However, our empirical evidence on the relationship between industry dynamics and productivity gives rise to the question whether entrepreneurship policy has potentially focused too much on hightech-sectors in recent years. Following the notion of the seminal paper by Jorgenson et al. (2008) our results suggest that lowtech-sectors are key drivers of productivity. We find that total business turbulence is the major driver of productivity development in lowtech sectors and substantially exceeds the effect of mere replacement of firms: a finding which cannot be confirmed for hightech sectors. Lowtech firms compete by adapting technology while being less able to deter competition with IP or R&D capacities.

Jorgenson et al. (2008) suggest that this technology adaption is a driver of competition and therefore of productivity growth. In order to foster industrial dynamics, policy makers should therefore extent their focus to lowtech firms. In their setting, Jorgenson et al. (2008) show that information technology diffusion was the major driver of US productivity growth in the mid-1990s. Today, digitalization and decarbonization constitute similar technological challenges. While it is clear that the technological frontier of these technologies is not reached yet, enabling across- and within-industry adaption and diffusion of these technologies will potentially be equally important in fostering business dynamics and productivity growth.

The mechanism identified by Jorgenson et al. (2008) sheds light on the challenges to firm turnover during and after the structural crises caused by the Corona pandemic. During the first phase, massive government support slowed the exit of firms with nonviable business models. Such companies continued to consume resources, which meant that valuable resources remained in these business models. In addition, such business models could compete with the help of government support, while young companies received limited support from governments. This leads to lower industrial dynamics. An important challenge for the post-pandemic period is to revive entry rates, stimulate technology adaptation, and adopt new business models as a basis for restoring or even increasing productivity growth above pre-crisis levels.

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1 Introduction

The decline in productivity growth over the last ten years (e.g. Bersch et al., 2018) as well as decreasing business dynamics in many industrialized countries are on top of the political agenda of many decision makers, fearing long-term impact on economic growth and employment. The coherence of these phenomena suggests a relationship between both, which calls for empirical evaluation on which economic policy can base decisions on. In this project we contribute to this debate and empirically investigate the evolution and relationship between industry dynamics and productivity development, identifying potential sources of concern and ways to address these. Understanding and anticipating interdependent competitor reactions to industry dynamics is critical to the evaluation of firm performance, since firm entry and exit fundamentally impact market structure and the competitive environment.

Over the last decades, the German government introduced a variety of political initiatives that aim at the reduction of barriers to market entry, including the established EXIST startup scholarships and the ERP startup loan from KfW, but also the INVEST Program and, more recently, the Green Startup Program. These programs aim at reducing the opportunity costs of starting businesses, facilitating market entry and ultimately providing innovation incentives for entrants by simplifying access to capital and industry-specific knowledge.

In recent years, the political debate not only on fostering market entry but also facilitating exit became more pronounced. Firm closure increasingly gained attention by policy makers as the fear of resource misallocation and potential "zombification" (McGowen et al., 2017) of Western economies have soared. But even before this debate, policy actions such as the German insolvency reform of 1999 targeted at facilitating exit for inefficient and indebted firms, by introducing a stricter insolvency declaration obligation ("Insolvenzanmeldepflicht") and a wider definition of insolvency and indebtedness.

However, while there has been a lively debate on the effectiveness of such programs to foster business dynamics since their launch in the 1980s, the direct impact of market entry and exit on incumbent firm performance and productivity has so far played a subordinate role in the evaluation of policy measures. Yet, whether an increase in business activity and dynamics that policy programs aim for actually leads to an increase in aggregate productivity should be a central criterion for policy measures.

The impact of market entry (and exit) on aggregate productivity is a-priori unclear in direction and magnitude, since entry impacts incumbent firms' productivity through various channels. These channels depend on factors such as demand in input and output markets and the competitive structure in the respective markets.

Investigating these aspects is especially interesting from a welfare point of view as higher level allocative efficiency implies that the economy is able to produce more at less costs. In that sense, Haltiwanger (2011) describes a "well-working" economy if it reveals (i) static allocative efficiency, i.e. more productive firms produce more, and (ii) dynamic allocative efficiency, i.e. over time input and/or output shares shift from less to more productive firms.

In this paper we focus on the impact of industry dynamics through market entry and exit on aggregate productivity growth. After a descriptive analysis of industrial and productivity dynamics in German industries, we decompose aggregate productivity growth into the contribution of incumbent firms as well as the contributions of entering and exiting firms. For this purpose, we follow the decomposition methodology proposed by Melitz and Polanec (2015) that allows to measure the contribution of firms' productivity improvements through learning effects as well as the contribution of resource allocation, i.e. changes in the distribution of inputs with respect to productivity and its impact on aggregate productivity growth. Moreover, the employed productivity decomposition methodology provides a measure of the impact of firm entry and exit on aggregate productivity growth.

Furthermore, we provide a reduced form analysis to evaluate the relationship between industry dynamics and incumbent firm productivity. We employ a unique dataset that combines detailed survey information on firms across different sectors in the German economy. In contrast to commonly used balance sheet data, this dataset allows us to control for different incumbent firm characteristics such as R&D expenditure and export activity. While currently entry is considered the most relevant variable in the scientific and political debate, we also consider business dynamics including exit and differentiate between replacement (churning) and total business dynamics (turbulence). The differential effect between turbulence and churning provides an indication on the role of structural change in firm stock, i.e. the total number of active firms.

The descriptive analysis provides evidence that industry dynamics has slowed down substantially in almost all parts of Germany and within most industries. A notable exception is constituted by the IT sector and the region of Berlin. The IT sector realizes the lowest decline in entry rates over time. The only sector with a similar stability in entry rates is hightech manufacturing, which also realizes the lowest entry rate in levels. Berlin has the highest variation and absolute levels of entry rates over time.

The decomposition analysis of aggregate productivity provides evidence for positive aggregate productivity growth during the period 2005-2018; but the growth rate slowed down substantially. Moreover, we find that aggregate productivity is higher for incumbent firms compared to entrants and exitors. Incumbents contribute most to the evolution of aggregate productivity. However, we find a substantial degree of allocative inefficiency among incumbents which hampers productivity growth. In particular, we find that labour shares are reallocated from more to less productive firms.

In the regression analysis, we link the evolution of industry and productivity dynamics. We find that by using 1-year lags for industry dynamics, none of the indicators for industry dynamics (entry rate, churning rate and turbulence rate) shows statistically significant coefficients. A short term association between firm dynamics and incumbent productivity is therefore not confirmed by our findings. As soon as we allow for longer time spans, using 4-year rolling averages of industry dynamics indicators, coefficients turn statistically significant and positive. The coefficient on turbulence has about twice the size of churning. Productivity dynamics seems to be substantially associated with overall business dynamics whilst only a smaller portion of these dynamics can be explained by mere replacement of firms and an at least equally large part of it can be associated to changes in firm stock.

The remainder of this project is structured as follows: in the second section, we explain our measure of productivity (labor productivity) and motivate our choice. In the third section, we provide descriptive evidence for industry dynamics. The fourth section presents the productivity decomposition approach as well as empirical results. In the fifth section, we conduct a reduced form regression analysis, which provides insights on the relationship between industry dynamics and incumbent firms' productivity. Section 6 concludes.

2 Productivity Measure

In recent years, productivity estimates have been employed to answer numerous research questions, e.g. the impact of trade legislations on productivity (Pavcnik, 2003; De Loecker, 2011), learning by exporting (De Loecker, 2013), or the impact of R&D on the firm-level productivity process (Doraszelski & Jaumandreu, 2013; Doraszelski & Jaumandreu, 2009). These papers employ Total Factor Productivity (TFPQ), which represents a factor neutral shifter in the firms' production function.

The estimation of TFPQ requires comparable input and output-quantities within and between firms, which is usually not available in standard balance sheet datasets. For this reason, many researchers estimate production functions using revenue and expenditure data, such as sales and material input expenditure. In this case, the productivity estimate is called Total Factor Revenue Productivity (TFPR).[2] TFPR and TFPQ are not the same measure, since TFPR also contains a price component, which is driven by supply and demand factors. Katayama, Lou and Tybout (2009) show that TFPR and TFPQ have different implications: TFPR does not necessarily react to external and internal shifters the way that TFPQ reacts.[3] An example is provided by De Loecker (2011): Evaluating the impact of changes in trade regimes on TFPR shows a different result than TFPQ, since a more liberal trade regime has a direct impact on prices, which constitutes a component to TFPR but not to TFPQ.

[2] Foster, Haltiwanger & Syverson (2008) provide a detailed comparison of TFPQ und TFPR.

[3] Klette & Griliches (1996) and De Loecker & Goldberg (2013) provide in depth explanations of the issues that occur with production function estimation given revenue data.

A productivity measure that imposes less data requirements than TFPQ/TFPR is labour productivity. Labour productivity relies on a single input factor, hence does not only represent a factor neutral shifter in the production function but also changes in factor intensity. As pointed out by Jorgenson et al. (2008), under the assumptions of constant returns to scale and competitive markets, labour productivity growth is driven by three components: capital deepening, labour quality growth, and changes in total factor productivity. The authors assume a value added Cobb-Douglas production function with labor and capital as inputs. If we assume that other input factors enter production, deepening of these factors would equally be reflected in the change in labour productivity growth. The authors define capital deepening as an increase in capital services per hour worked, which captures changes in productivity that is driven by the availability of better and more capital goods. Labour quality represents the composition of the work force; more educated workers that are familiar with the production process positively affect productivity growth. Total factor productivity, as previously described, captures factor neutral shifters that drive productivity.

The goal of this study is to evaluate the impact of market entry and exit on incumbent firm productivity. Estimating TFPQ/TFPR in this setting creates a substantial sample selection towards larger firms, since small firms do not report sufficient balance sheet information to estimate these productivity measures. We expect that market entry and exit affects smaller firms more substantially than for instance multinational companies. To keep smaller firms in the sample, we choose labour productivity as productivity measure.

3 Aggregate Industry Dynamics

3.1 Data

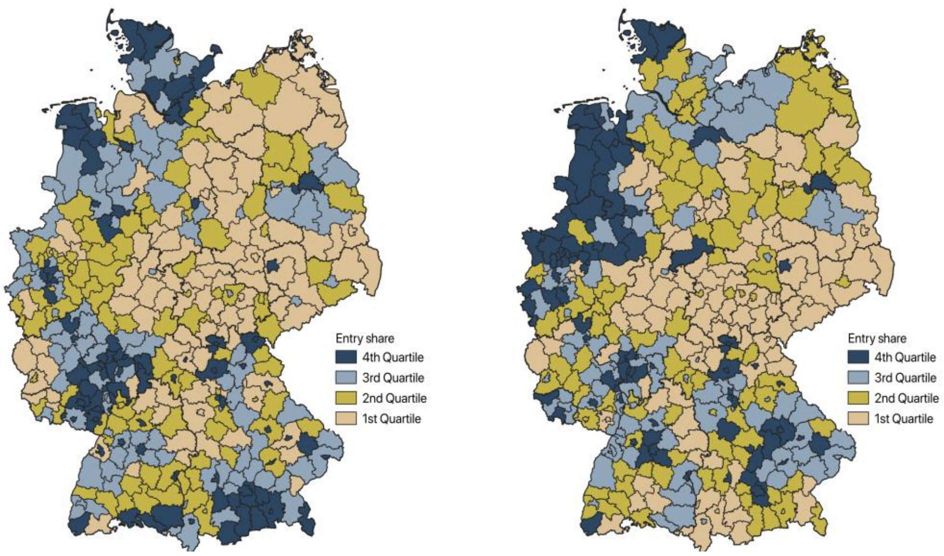
We draw firm dynamics data from the Mannheim Enterprise Panel (MUP) hosted by ZEW. The Mannheim Enterprise Panel (MUP) is the most comprehensive microdata base of companies in Germany (see Bersch et al., 2014). Twice a year, the credit agency Creditreform transmits a complete extract of its extensive database to ZEW for scientific purposes. Creditreform records all companies in Germany that are economically active to a "sufficient degree".

The MUP represents the full population of companies in Germany - including microenterprises and self-employed freelancers. In order to make the business data usable as a panel and, in particular, to determine annual firm entries and closures, the data undergoes various processing steps at ZEW. Notably, information about the number of startups is not readily available when the data is transmitted from Creditreform to ZEW. Therefore, processing steps are necessary to make the data suitable for an analysis of industry dynamics. Among the challenges that ZEW faces in preparing the data is that startups are captured with a certain lag in Creditreform data, which leads to an underrepresentation of young firms in MUP for most recent years. In order to overcome this underrepresentation, ZEW employs an extrapolation procedure that has been improved continuously to ensure precision of extrapolation.

3.2 Regional Variation in Entry and Exit Rates

First, we evaluate the regional distribution of market entry and exit across all sectors. Since the absolute number of entry per region does not provide comparable information due to differences in district sizes and working population, we employ two different weights: 1) The amount of eligible working population in the respective region 2) The amount of existing firms. Figure 1 shows both indicators for market entry in Germany. The maps depict the percentiles of the entry distribution for each state during the observation period. Taking Berlin as an example, both maps show that the market entry rate in Berlin is higher than at least 75% of all districts in Germany, independent of the weights we choose (working population or number of firms).

Figure 1: Quartile distribution of Entry Intensities (entry weighted by population aged 18 to 65) on the left and Entry Rates (number of entrants as a share of incumbent firms) on the right by German Kreise 2005-2019.



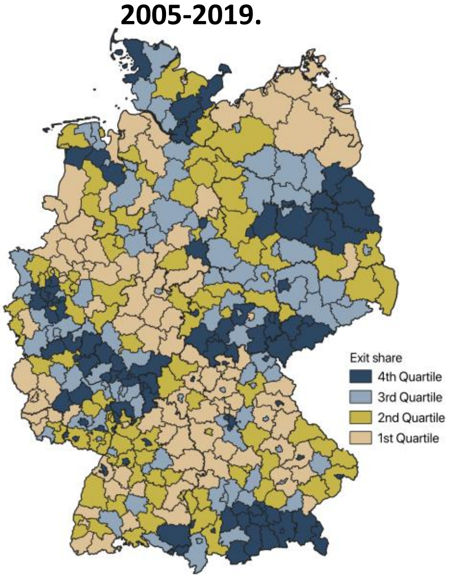
Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

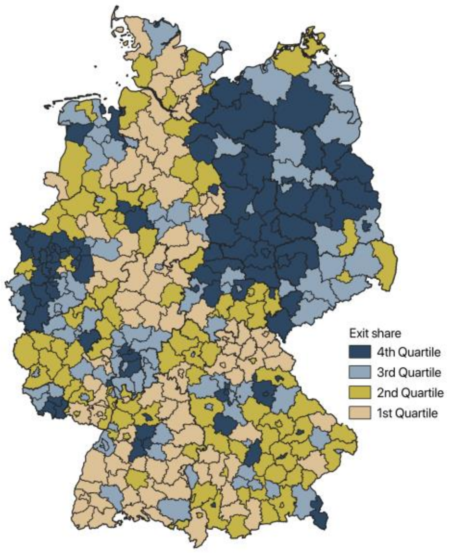
Both indicators show a concentration of entrants around the larger agglomerations primarily in Western Germany with the exception of Berlin and its adjacent regions.

Figure 2 shows the same maps for market exit. Again, the map to the left illustrates the exit rates weighted by the total amount of eligible working population, whereas the quartiles in the right map are weighted by the total amount of firms in the respective district.

Comparing Figure 1 and Figure 2 shows a different pattern for the market exit rates, which is primarily driven by exits in districts of Eastern Germany. This pattern is stronger for the exit rates weighted by the amount of existing firms

Figure 2: Quartile distribution of Exit Intensities (exit weighted by population aged 18 to 65) on the left and Exit Rates (number of exits as a share of incumbent firms) on the right by German Kreise 2005-2019.





Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

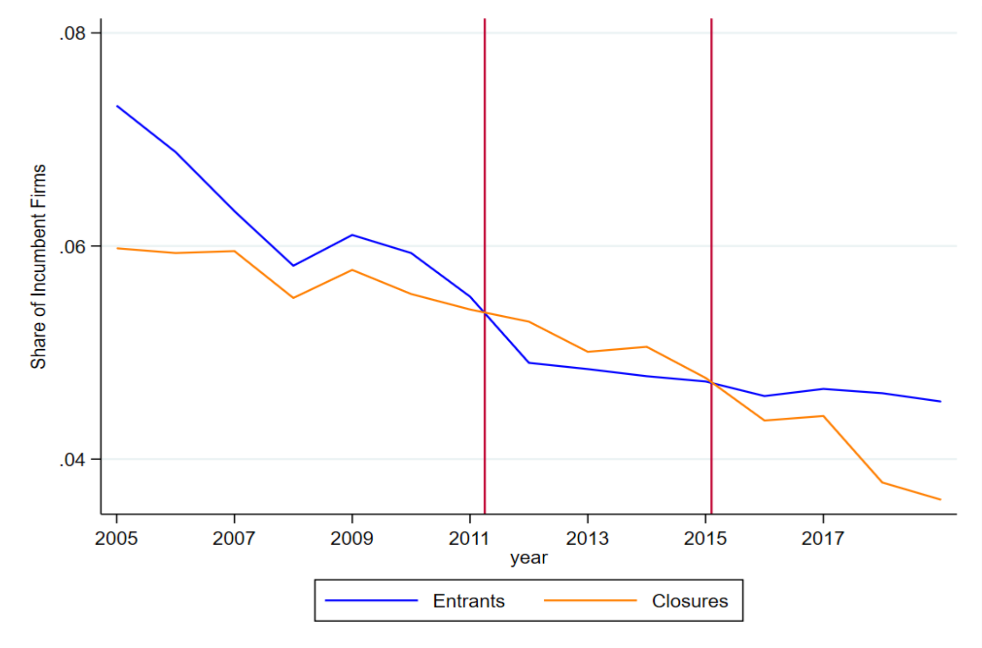
in the respective districts. A similarity to Figure 1 is the strong concentration of exit in the larger agglomeration regions.

Figure 1 and Figure 2 confirm the prevailing expectation that the highest industry dynamics take place in industrial conurbations and less in rural areas.[4]

3.3 Time Variation in Entry and Exit Rates - Total

We observe a strong decline in exit and entry rates over time. This is illustrated by Figure 3. Until 2011, the entry rate across industries was higher than the exit rate. Between 2011 and 2015, this relationship has reversed, such that more

Figure 3: Entry and Exit (Closure) Rates (as a share of incumbent firms) in Germany between 2005 and 2019



Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

firms exited the market than entered. From 2015 on, we observe a stronger entry than exit rate again. Nevertheless, the overall pattern of both lines shows

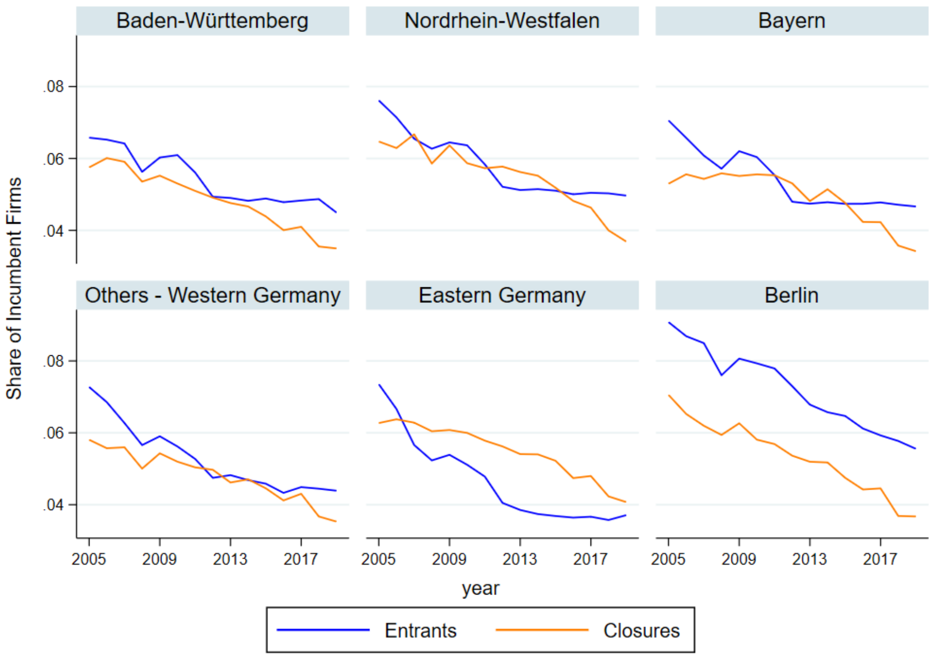
[4] Appendix A contains industry specific maps for the exit and entry rates across Germany.

that entry has experienced a stronger decrease than exit, implying a decrease in the total number of active firms. The total number of entrants decreased from 205.978 in 2005 to 132.855 Startups in 2019. The total number of exiting firms decreased from 168.289 to 105.882 firms within the same time frame.

3.4 Time Variations in Entry and Exit Rates - Across Regions

Taking into account the time variation of exit and entry rates across regions, Figure 4 confirms the tentative evidence from the maps in Figure 1 and Figure 2: In Eastern Germany (without Berlin), we observe a higher exit than entry rate already from 2005 on. This relationship holds until the end of our observation period. Berlin, in contrast, represents an outlier in our dataset. Over the full

Figure 4: Entry and Exit (Closure) Rates (as a share of incumbent firms) in selected German States between 2005 and 2018.



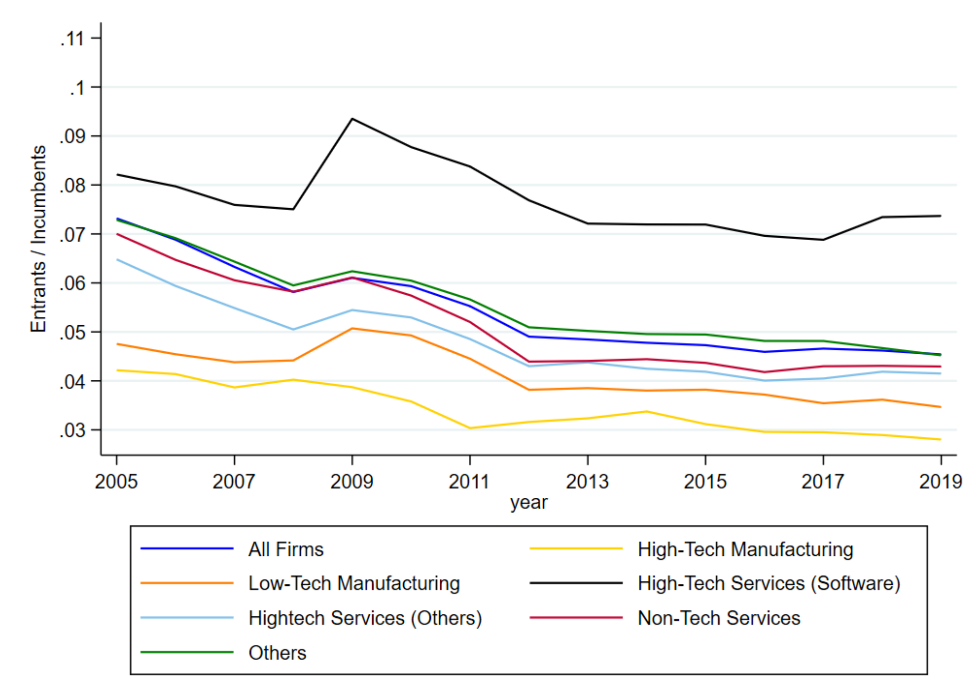
Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

observation period, the entry rate stays roughly 2% higher than the exit rate. In other states, we observe the reverse in relationship as in Figure 2.

3.5 Time Variations in Entry and Exit Rates - Across Sectors

In this section, we have a closer look at the time variation of entry and exit rates in Figure 5 and Figure 6. Figure 5 depicts entry rates across sectors and time. We observe the highest and most stable entry rate for the IT-sector (between 8-9%). The only other sector with a similar stability in entry rates is hightech manufacturing (entry rate around 4-3%), which also realizes the lowest entry rate in levels. Moreover, we observe a very similar pattern of entry rates in

Figure 5: Entry Rates by technology sector between 2005 and 2019.

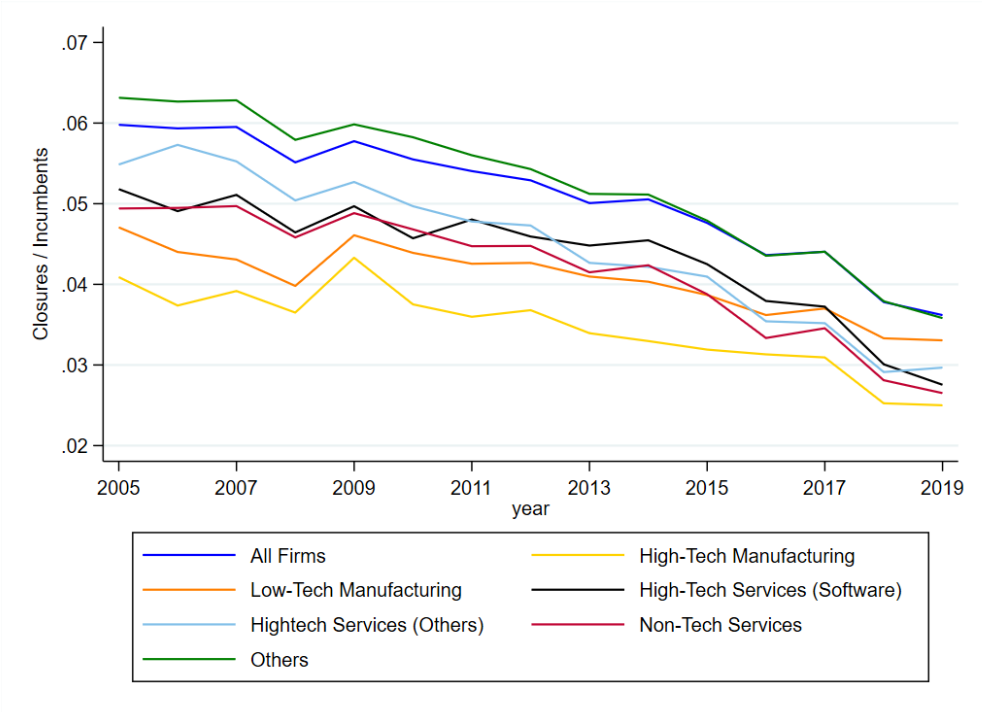


Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

levels and decline over time for the remaining sectors which realize an entry rate between 7-4%.

Figure 6 illustrates the exit rates across sectors and time. All sectors show a decline in exit rates which varies between 1-3%. “Others” which contains firms in the trade segment, realizes the highest exit rate in levels over time. This is closely followed by the exit rate of hightech services (Others) and hightech services (Software). Lowtech services realize the lowest exit rate during our observation period.

Figure 6: Exit Rates by technology sectors between 2005 and 2019.

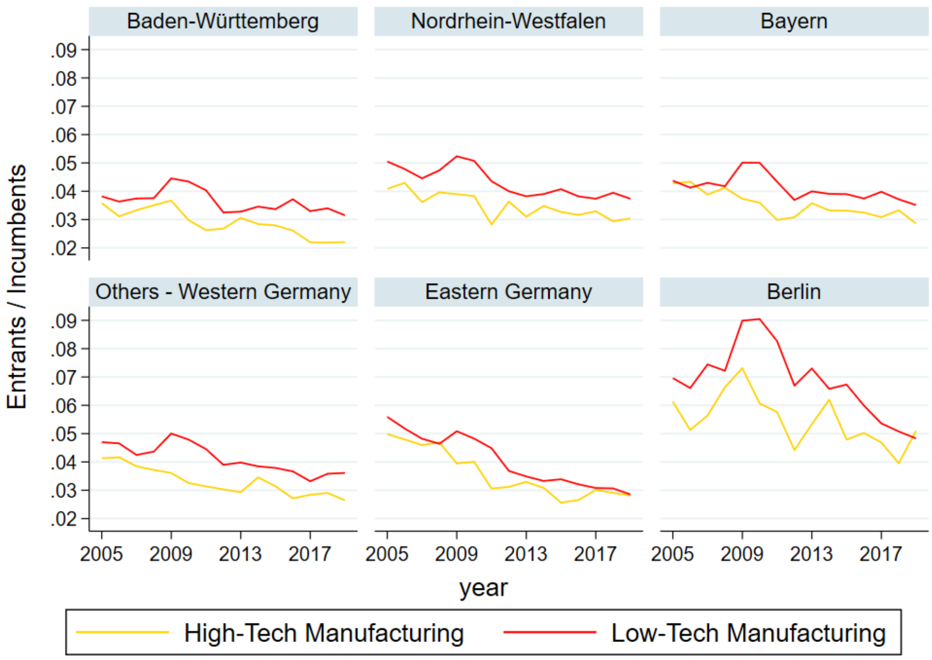


Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

3.6 Time Variations in Entry and Exit Rates - Across Sectors, Regions and Time.

In this section, we compare entry (Figure 7) and exit (Figure 8) rates of the manufacturing sector across regions and over time. Following the procedure in the previous section, we divide the manufacturing sector in two subcategories: Hightech and lowtech manufacturing. Figure 7 shows the entry rate of both subcategories. We observe a higher entry rate for lowtech manufacturing firms than hightech manufacturing firms over time and regions during the full observation period. For two of the largest states in Germany, Baden-

Figure 7: Entry Rates in Hightech and Lowtech Manufacturing Sectors in selected German States.

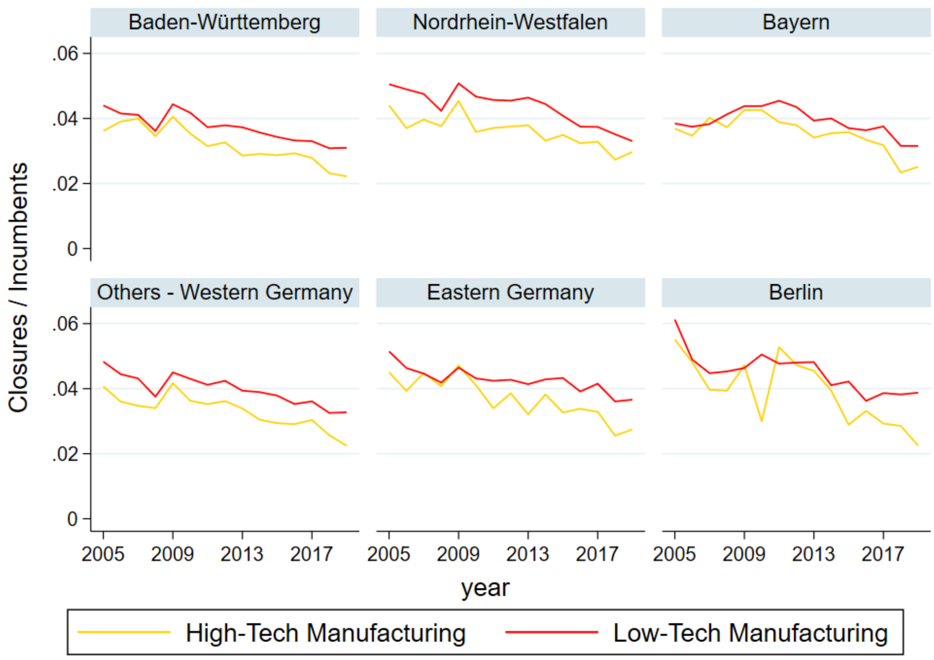


Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

Württemberg and Bayern, we observe a relatively stable entry and exit rate. Nordrhein-Westfalen shows a slight decrease in entry of both hightech and lowtech manufacturing of roughly 2%. A different pattern is observed in Eastern Germany and Berlin in particular. For Eastern Germany, we observe a steep decline in both manufacturing sectors of roughly 4% during the observation period. In Berlin, the variation and absolute levels of entry rates over time is particularly large compared to the other regions. The highest entry rate for lowtech manufacturing in Berlin was realized around 2009 and amounted to an entry rate of 9%, whereas the highest entry rate for hightech manufacturing was realized in 2004 with roughly 8% entry.

Figure 8 illustrates the exit rates for hightech and lowtech manufacturing firms across regions and time. Similar to entry rates, all States show a downward

Figure 8: Exit Rates in Hightech and Lowtech Manufacturing Sectors in selected German States.



Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

trend in exit rates in both hightech and lowtech manufacturing while the rates are almost always higher in lowtech sectors. The highest fluctuations are found for Berlin around the years of the crisis of 2008 and 2009. The State of Bayern showed an increase in rates between 2005 and 2009 but since then also is characterized by a downward trend.

4 Aggregate Productivity Dynamics

4.1 Data

In this section, we employ a novel dataset constructed by Lubczyk and Peters (2020). We refer to this paper for a detailed description on the dataset construction. The dataset consists of two surveys that are conducted at the ZEW Leibniz-Centre for European Economic Research in Mannheim: 1) The Mannheim Innovation Panel (MIP), 2) The IAB/ZEW Mannheim Startup Panel (MSP).

The MIP is one of two surveys that are conducted at the ZEW Leibniz-Centre for European Economic Research. This survey was first initiated in 1993 and constitutes the German part of the European-wide Community Innovation Survey (CIS).

The survey targets firms from four broad groups of industries, which are manufacturing, mining, energy and water supply, and services. Within these industries, the survey covers all firms that have five or more employees and that are legally independent units with their headquarters based in Germany.

The MSP is the second and more recently launched survey that is conducted at the ZEW Leibniz-Centre for European Economic Research. This survey was conducted jointly with the KfW banking group from 2008 to 2013. In 2015, the German Federal Employment Agency (IAB) took over KfW's part as collaborator. The panel annually surveys newly established firms in Germany. The goal is to follow new startup companies during the first eight years of their existence and gather information about their business activity. After eight years, the companies leave the Startup Panel. This survey covers firms from all economic sectors except primary, public, and energy sectors.

The combination of these datasets allows us to observe labour productivity for startup companies as well as established firms. Moreover, we observe the exact date of firm entry, closures as well as the reason for the choice of closure. This information grants an advantage compared to standard balance sheet data: Information on entry and exit are provided by the respective firms directly. The combined dataset covers the time period between 2005 and 2018. For the analysis of aggregate productivity dynamics, we only consider a subdataset of firms with non-missing and non-negative values for labour productivity. This leaves us with a sample that contains 163,712 observations for 42,156 firms.

As we conduct an aggregate productivity decomposition with a special focus on firm entry and exit, we distinguish between different groups of firms: survivors, entrants, and exitors. Each firm belongs to one of these groups. In the following section, we describe the terminology which we employ to allocate firms to the respective groups.

4.1.1 Measuring Entry and Exit - Yearly Changes

We begin by defining three firm status, denoted by the variable $status_{it}$. This variable takes the value of zero ($status_{it} = 0$) if a firm is either created at time t or is not older than two years. The variable takes the value of one ($status_{it} = 1$) if the firm' existed for longer than two years. The variable takes the value two ($status_{it} = 2$) if a firm is about to exit the market.

Based on the constructed status variable, we further define binary variables for entry (E_{it}), survival (S_{it}) and exit (X_{it}). We define firm entry $E_{it} = 1$ if and only if $status_{it} = 0$. Firm survival is defined by $S_{it} = 1$ if $status_{it} = 1$ or $status_{it} = 2$ and $status_{i,t+1} = 2$. Note that for some firms, we observe $status_{it} = 2$ for several consecutive years. This implies that firms are active while bankruptcy proceedings are ongoing. According to our definition, a firm is defined as a survivor as long as this process is ongoing. Exit is then consequently given by $X_{it} = 1$ if $status_{it} = 2$ and $status_{i,t+1} = \emptyset$. Thus, exit is measured at the year prior to the effective exit.

4.1.2 Measuring Firm Entry and Exit over longer Time Spans

Since we measure productivity growth not only from year to year but also between time spans longer than one year (between $t - k$ and t), we create an additional definition of firm survival, entry and exit for time spans longer than one year.

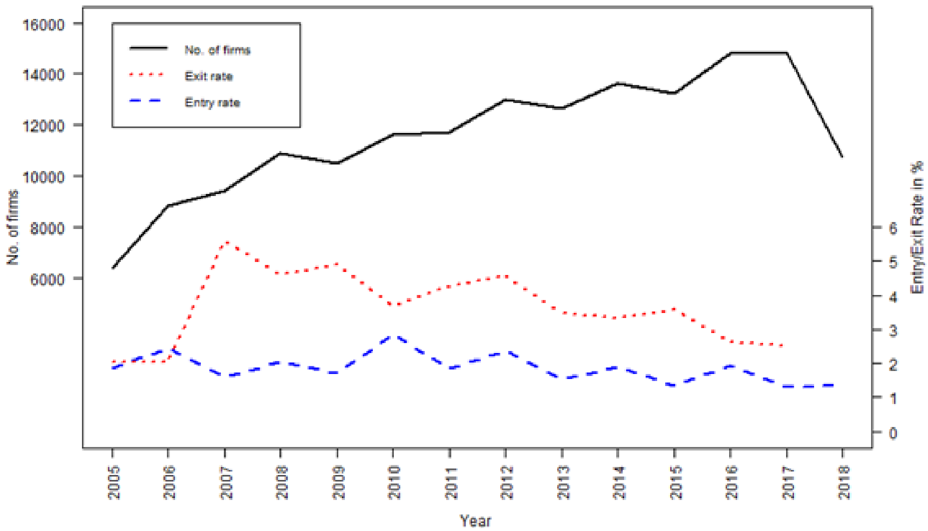
In this section, we define firms as survivor between $t - k$ and t, if the firm is active both at $t - k$ and at t. Furthermore, a firm is defined as an exitor if the firm exited the market between the two periods, i.e. if $X_{is} = 1$, for some s with $t - k \leq s < t$, implying that the firm was active at $t - k$ but not at t. A firm is defined as an entrant if the firm entered the market between the two periods, i.e. if $E_{is} = 1$, for some s with $t - k < s \leq t$, implying that the firm was inactive at $t - k$ but active at t.

4.1.3 Firm Dynamics over Time - Subdataset

Since the decomposition analysis is based on a subsample of firms of the German economy, we explore the sample specific firm-dynamics and its deviation from the dynamic of all firms (Section 3) in this section.

Figure 9 shows the evolution of the number of firms and entry/exit rates across industries and regions. A particularity of the data is that the number of observed firms increases while entry and exit rates are relatively stable.

Figure 9: Evolution of entry, exit and number of firms in the compound dataset.



Source: Mannheim Innovation Panel (MIP), IAB/ZEW-Startup Panel (SUP), 2020 – Own Calculations.

While in 2005 our sample consists of roughly 6400 firms, we observe about 10800 firms in 2018. The exit rate is highest in 2007, given by roughly 5.5%, and decreases to roughly 2.5% in 2018. The entry rate remains relatively stable, ranging mostly between 1.2% and 2.0%.

4.2 Productivity Decomposition

We consider an industry with a total of N firms that are indexed by i and operate at time t. Most studies in the literature measure an industry's aggregate productivity by a weighted average of individual firms' productivity, weighted by a context-specific weight, such as market shares or labour shares. As we measure and decompose aggregate labour productivity, we use firms' labour share as weights, i.e. firms share of employment w.r.t. total employment in the industry.

Formally, aggregate productivity is given by:

$$\Phi_t = \sum_{i=1}^{N_t} s_{it}\phi_{it}, \tag{1}$$

where Φ_t denotes aggregate productivity at time t, ϕ_{it} and s_{it} represent individual firm's log labour productivity and share, respectively.

The seminal work by Olley and Pakes (1996) shows that aggregate productivity, expressed as a weighted average, can be decomposed into two components, given by:

$$\Phi_t = \sum_{i=1}^{N_t} s_{it}\phi_{it} = \overline{\phi_t} + \sum_{i=1}^{N_t}(s_{it} - \overline{s_t})(\phi_{it} - \overline{\phi_t}), \tag{2}$$

where ϕ_t and s_t denote the respective unweighted averages. Equation (2) can be derived from equation (1) simply by extending (1) to $\sum_{i=1}^{N_t}(s_{it} + \overline{s_t} - \overline{s_t})(\phi_{it} + \overline{\phi_t} - \overline{\phi_t})$. This equation can be reformulated to (2).

Equation (2) shows that aggregate productivity is driven by two components: The first component of equation (2), which represents the industry's unweighted productivity average. The second component of equation (2), which represents the covariance between firms' labour productivity and labour shares.

Given that ϕ_{it} is measured in logs, we estimate aggregate productivity growth by taking the first difference between two periods, i.e. $\Delta\Phi = \Phi_t - \Phi_{t-k}$. As a consequence of the above description, aggregate productivity growth is driven by (i) a change in firms' unweighted average, called the *within* change, i.e $\Delta\overline{\phi}$

(referred to firms productivity improvement through learning) and (ii) a change in firms covariance between productivity and the labour share, called the *between* change, i.e. $\Delta \sum_{i=1}^{N}(s_i - \bar{s})(\phi_i - \bar{\phi})$ (referred aggregate productivity growth through the process of resource reallocation).

The Olley-Pakes productivity decomposition is usually employed for static evaluations, i.e. in settings where the same set of firms is active during the full observation period. However, since we focus on the evaluation of aggregate productivity development that is also driven by firm dynamics, we employ the procedure by Melitz and Polanec (2015). The authors extend the Olley-Pakes decomposition, which they refer to as the Dynamic Olley-Pakes Productivity Decomposition (DOPD, henceforth).

More specifically, consider two arbitrary periods, $t-k$ and t. The set of firms active at $t-k$ is composed of firms that either survive or exit until t. Instead, at t the set of active firms is composed of firms that have survived and firms that have entered the market between $t-k$ and t.

According the DOPD approach, aggregate labour productivity at $t-k$ and t is given by equation (4) and (5) respectively:

$$\Phi_{t-k} = S_{S,t-k}\Phi_{S,t-k} + S_{X,t-k}\Phi_{X,t-k} = \Phi_{S,t-k} + S_{X,t-k}(\Phi_{X,t-k} - \Phi_{S,t-k}) \quad (4)$$

$$\Phi_t = S_{S,t}\Phi_{S,t} + S_{E,t}\Phi_{E,t} = \Phi_{S,t} + S_{E,t}(\Phi_{E,t} - \Phi_{S,t}) \quad (5)$$

where $S_{G,t} = \sum_{i\in G}^{N_t} s_{it}$ and $\Phi_{G,t} = \sum_{i\in G}^{N_t}(s_{it}/S_{G,t})\,\phi_{it}$ denote the aggregate labour share and aggregate labour productivity, of group $G = \{E, S, X\}$, with E, S, and X referring to the group of entrants, survivors, and exitors. Note that the second equality of equations (4) and (5) are derived by adding $S_{X,t-k}\Phi_{S,t-k} - S_{X,t-k}\Phi_{S,t-k}$ and $S_{E,t}\Phi_{S,t} - S_{E,t}\Phi_{S,t}$ respectively and using the fact that aggregate market shares of survivors and exitors (entrants) at $t-k$ (t) sum up to one, i.e. $S_{S,t-k} + S_{X,t-k} = 1$ $(S_{S,t} + S_{E,t} = 1)$.

Using the insights from equation (4) and (5), we define aggregate productivity growth as the following:

$$\Delta\Phi = \left(\Phi_{S,t} - \Phi_{S,t-k}\right) + \mathrm{S}_{E,t}\left(\Phi_{E,t} - \Phi_{S,t}\right) + \mathrm{S}_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k})\,, \quad (6)$$

Equation (6) shows that surviving firms only contribute positively to aggregate productivity growth if survivors' aggregate productivity is higher at t compared to $t-k$, i.e $\left(\Phi_{S,t} - \Phi_{S,t-k}\right) > 0$. Entrants contribute positively to aggregate productivity growth if their level of aggregate productivity is higher compared to the aggregate level of the group of surviving firms, i.e $\left(\Phi_{E,t} - \Phi_{S,t}\right) > 0$, and exitors contribute positively to aggregate productivity growth if that group's aggregate productivity is lower compared to the aggregate productivity of the group of surviving firms, i.e $(\Phi_{S,t-k} - \Phi_{X,t-k}) > 0.$>0. Exitors contribute positively to aggregate productivity growth if their aggregate productivity is higher compared to the aggregate productivity of surviving firms, i.e. $\Phi_{E,t} - \Phi_{S,t} > 0$. Similary, exitors only contribute positively to aggregate productivity growth if their aggregate productivity is smaller compared to the aggregate measure of the group of surviving firms, i.e. $(\Phi_{S,t-k} - \Phi_{X,t-k}) > 0.$

Decomposing surviving firms' contribution into their *within* and *between* contribution (as in equation (2)), we obtain the final aggregate productivity decomposition, which is given by equation (3):

$$\Delta\Phi = \Delta\,\overline{\phi_s} + \Delta N_S cov_s \; + \; S_{E,t}\left(\Phi_{E,t} - \Phi_{S,t}\right) + \; S_{X,t-k}\left(\Phi_{S,t-k} - \Phi_{X,t-k}\right), \quad (7)$$

where $\Delta\,\overline{\phi_s}$ and $\Delta N_S cov_s$ denote the *within* and *between* growth contribution of surviving firms.

4.3 Discussion

Evaluating the development of aggregate productivity cleared from variation in productivity that is driven by market entry and exit has been central in numerous papers that precede the contribution by Melitz & Polanec (2015). These are for instance the papers by Baily, Hulten, and Campbell (1992) (BHC), Griliches and Regev (1995) (GR), and Foster et al. (2001) (FHK).

These papers rely on a weighted average of the productivity measure, where the weight is defined as the firms' market shares. In doing so, the weighted average allows to track changes in both firms' productivity and market shares, i.e. measuring learning and reallocation effects among incumbent firms, as well as the impact of firm entry and exit on the aggregate productivity development. In contrast to the method presented by BHC, both GR and FHK introduce a reference average productivity level to which the aggregate productivity level of incumbents, entrants, and exiting firms is compared, and which is crucial to measure the respective group's impact on overall aggregate productivity development. Melitz and Polanec (2015) discuss and compare these methods in detail. The authors argue that their DOPD approach more accurately measures the contribution of each firm group, where the reference level is represented by the aggregate productivity of the group of surviving firms.

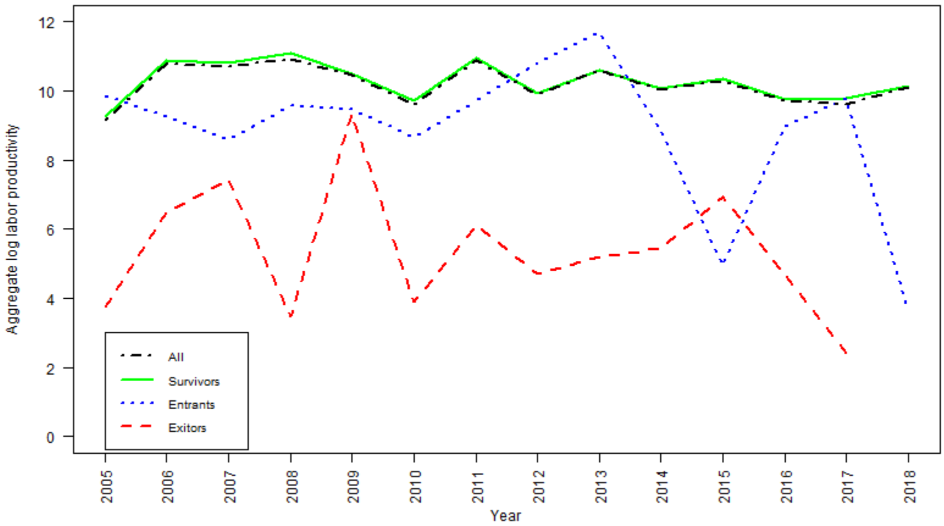
Besides the firms' market shares, there exists a range of other weights that are employed for the evaluation of aggregate productivity development. These typically depend on the respective productivity measure that is estimated. In the case of Total Factor Productivity (TFPQ/TFPR), the standard in the literature is to use firms' output/sales shares for the weighted average of aggregate productivity. When firms' productivity is measured as labour productivity (as in this project) the standard in the literature is to use employment shares. (Foster et al. 2001; Van Biesebroeck, 2008; Melitz and Polanec, 2015). Foster et al. (2001, p. 318) discuss the choices and their impact of the respective weights in detail, arguing that for labour productivity *"the seemingly appropriate weight is employment since this will yield a tight measurement link between most measures of labor productivity using industry-level data and industry based measures built up from plant-level data."*

4.4 Empirical Results

Figure 10 illustrates the evolution of productivity of the three firm groups (survivors, entrants, and exitors) and aggregate productivity. Aggregate productivity of surviving firms is illustrated by the green line, which shows that aggregate productivity growth is relatively stable. The black line represents aggregate productivity growth of all firms, which closely follows the productivity evolution of surviving firms. Moreover, we observe that the largest part of overall productivity growth is contributed by survivors. Aggregate productivity of entrants and exitors is more volatile and below the level of surviving firms.

To asses productivity growth for the three groups, we consider time intervals of four years, defined by 2005-2008, 2008-2011, 2011-2014, and 2015-2018 and conduct the DOPC as described in the previous section.

Figure 10: Evolution of Productivity of the three firm groups and aggregate productivity



Source: Mannheim Innovation Panel (MIP), IAB/ZEW-Startup Panel (SUP), 2020 – Own Calculations.

Table 1 presents the results of the productivity decomposition. First, we evaluate the second column, which reports total growth rates (over all firm groups). During the first two periods, 2005-2008 and 2008-2011, aggregate productivity growth is relatively high (11.37 % and 10.26 % respectively). During the latter two periods, 2011-2014 and 2015-2018, the growth rate drops to 2.46 % and 2.25 %, respectively. Having a closer look at the different contributors to aggregate productivity growth, we measure that survivors contribute most to overall growth. The contribution of survivors to productivity growth is further decomposed into the *within* and *between* growth contribution. During the observation period, the *within* growth contribution is positive, indicating that on average firms have increased their productivity. This is related to a positive learning effect and/or by better adapting to the prevailing economic environment. Surviving firms' *between* growth contribution is negative for all periods except 2008-2011. A negative *between* growth contribution is related to inefficiency in the reallocation process (Haltiwanger, 2011); meaning labour shares shift from higher to less productive firms, which decreases the overall aggregate productivity growth. More precisely, for the period 2005-2008, the *within* contribution is given by 16.91 % while the *between* contribution is given by -6.85%. Likewise for the periods 2011-2014 and 2015-2018, where we measure a positive within contribution given by 8.74 % and 13.75 %, the negative *between* contribution, given by -7.49 % and -12.84 %, considerably hampers total aggregate productivity growth. Generally, a more important within contribution goes in line with other findings in the literature (De Monte, 2021; Hassin, 2019; Baily et. al., 1992; Foster et al., 2001).

The contribution of entrants and exitors is minor compared to surviving firms. This is not surprising since their contribution is weighted by each group's (aggregate) labour share. Table 2 shows both aggregate productivity and labour share measured at the initial year (Panel A) and at the last year (Panel B) of each period. Surviving firms generally detain at least 96 % of total labor. Consequently, exitors and entrants detain only a very small share.

Labor shares of entrants are particularly small, which leads to a marginal contribution to aggregate productivity growth. A negative sign in the contribution of entrants indicates, however, that entrants' aggregate productivity is smaller compared to survivors. Exitors contribute positively to aggregate productivity growth, indicating that this group's aggregate productivity is lower compared to the group of surviving firms. Note that higher productivity levels of survivors compared to entrants and exitors are also reflected in the respective aggregate productivity measures, illustrated in Table 2.

For some periods, the contribution to aggregate productivity growth by exiting firms is relatively large. For instance, for the period 2008-2011, this group contributes to aggregate productivity growth roughly 3.88%, which is comparable to the within growth contribution of surviving firms in the same period.

Measuring a negative (positive) contribution to aggregate productivity growth of entrants (exitors) is intuitive: On the one hand, entering firms lack in skills and experience compared to incumbent (or surviving) firms, which is also reflected in entrants' productivity. On the other hand, exitors are less productive and thus self-select into exit once they drop below a certain productivity threshold (see Jovanovic (1982) and Ericson and Pakes (1995) for theoretical foundations on that issue). This implies that as soon as they leave the market, aggregate productivity increases. Similar findings are documented by Farinas et al. (2005) for Spanish manufacturing and Wagner (2010) for German manufacturing.

Table 1: Aggregate productivity decomposition with firm entry and exit.

	Total	Contribution Survivors		Contribution	Contribution
Period	Growth	Within	Between	Entrants	Exitors
2005 - 2008	11,37	16,91	-6,85	-0,74	2,04
2008 - 2011	10,26	5,41	1,84	-0,88	3,88
2011 - 2014	2,46	8,74	-7,49	-0,70	1,91
2015 - 2018	2,25	13,75	-12,84	-0,23	1,56

Note: All figures represent growth rates in % for the respective period.

Table 2: Aggregate labour productivity and aggregate labour shares.

Panel A: Measures at $t-k$							
$t-k$	t	$\Phi_{S,t-k}$	$S_{S,t-k}$	$\Phi_{X,t-k}$	$S_{X,t-k}$	# Surv.	# Exit.
2005	2008	12,21	96,36	11,64	3,64	3332	455
2008	2011	12,44	96,30	11,39	3,70	5552	1020
2011	2014	12,57	97,58	11,78	2,42	4926	1148
2015	2018	12,63	97,99	11,85	2,01	4730	979
Panel B: Measures at t							
$t-k$	t	$\Phi_{S,t}$	$S_{S,t}$	$\Phi_{E,t}$	$S_{E,t}$	# Surv.	#Entr.
2005	2008	12,31	96,73	12,08	3,27	3332	434
2008	2011	12,51	98,87	11,73	1,13	5552	240
2011	2014	12,58	99,03	11,86	0,97	4926	345
2015	2018	12,63	98,92	12,43	1,08	4730	186

Note: The columns $\Phi_{G,j}$ and $S_{G,j}$ with $G = \{S, X, E\}$ and $j = \{i, j\}$, denote the aggregate labour productivity and labour shares of the firm groups survivors, entrants, and exitors - measures at the initial year $(t-k)$ and the last year(t). Aggregate labour shares are given in %.

5 Relationship between Productivity and Firm Dynamics

In this section, we link the descriptive evidence from Section 3 on industry dynamics and Section 4 on productivity development. The question we pose is: What is the impact of market entry on incumbent firm productivity? Unlike the popularity of the concept of Schumpeterian creative destruction would suggest - that describes the dynamic reaction of established firms to entry - empirical evidence on the concept is rather limited.

Important exceptions are studies by Aghion and Bessonova (2006), Aghion et al. (2009), Czarnitzki et al. (2008) and Greenstone et al. (2010). These studies investigate sophisticated entry by advanced, innovative or larger firms. We are aware of only two studies that look into the effect of all business formations (i.e. “everyday-Entrepreneurship” (Welter et al., 2016) on productivity, namely studies by Andersson et al. (2012) who look at Swedish firm data and Fritsch and Changoluisa (2017). The latter study constitutes the most relevant and recent empirical work on the topic for Germany.

While the empirical question that Fritsch and Changoluisa (2017) ask is similar to ours, the setting they choose as well as the data inherit noteworthy differences which makes our analysis a further contribution to the topic. To highlight only three major differences, we first look at all firms in Germany and not only in Western Germany. Second, we employ a dataset which includes substantially smaller firms than the IAB establishment panel used in their study. We believe that including smaller firms makes a difference because smaller firms usually have less resources, inherit less flexible and often hardly scalable supply chains, and are characterized by weaker networks across regions to react to entry. Third and last, our study not only looks at firm entry but also at overall business turbulence (entry and exit) in a region and industry.

We believe that the evaluation of entry alone is not sufficient to capture business dynamics, since many business establishment result from so called “revolving-door” entries (Audretsch and Fritsch, 2002), i.e. entrants e.g. of retailers that result immediately from the closure of the former proprietor (replacements). Our analysis therefore differentiates between the industry dynamics measures entry rate, churning rate (the rate of replacements), and turbulence rate, the average share of both entry and exit over firm stock. All variables employed are described in detail in the next subsection.

A priori, there is no clear theoretical answer on the direction of the effect of entry on productivity. Startups challenge incumbents by taking over parts of their market shares, which, reduces the incumbents' productivity if they do not appropriately react with respect to their input decisions. However, the competitive pressure induced by startups also incentivizes incumbents to improve their production efficiency (top dog), which in other words leads to productivity gains. Empirical studies mostly show a positive effect of firm dynamics on productivity in the long run. Our results are mostly in line with previous literature. Similar to Fritsch and Changoluisa (2017) we find no significant effect in the short run but positive effects in the long run.

5.1 Data and Methodology

In order to analyse the relationship between industry dynamics and firm-level productivity, we combine the datasets used in section 2 and 3 of this report. Namely, our firm-level data is drawn from the joint sample of firms from the Mannheim Innovation Panel (MIP) for older firms and the IAB/ZEW Startup Panel (SUP) for younger firms. From this data we retrieve our firm-level productivity measure and control variables. In a next step, we merge industry dynamics data from the Mannheim Enterprise Panel (MUP) by using the firms' 2-digit NACE-code, the labour market region it is situated in (AMR) as well as the respective year of operation. In the next section, the variables employed in our analysis are explained in detail.

5.1.1 Variable Description

The most important firm-level variable we employ is labour productivity which is defined the way it was in the previous chapter 3. We use the natural logarithm of firm-level productivity (and of the respective explanatory variables indicators) in order to be able to interpret the results as elasticities. On the firm-level, we use age, export activity, and R&D expenditures as control variables. The methodology section in 5.2 provides a detailed description of the regression specifications that we take to the data.

Since market entry and exit are strongly correlated (see Appendix C), we do not include both measures separately in the regression analysis, as this would increase standard errors through multicollinearity and complicates reasonable interpretations of the regression coefficients. Instead, we employ three different compound measures as already noted in the introductory part of this section: The entry rate, churning rate (replacement) and turbulence rate.

The variables $entry_{rst}$ and $exit_{rst}$ denote the observed total number of firm entries and exits for a given labour market region r and *2-digit NACE* sector s. The variable $stock_{rst}$ indicates the total number of active firms, including incumbent, entering, and exiting firms.

1. Entry Rate

$$entry\ rate_{rst} = \frac{entry_{rst}}{stock_{rst}}$$

2. Churning Rate

$$churning\ rate_{rst} = \frac{entry_{rst} + exit_{rst} - |\,entry_{rst} - exit_{rst}\,|}{2 \cdot stock_{rst}}$$

3. Turbulence Rate

$$turbulance\ rate_{rst} = \frac{entry_{rst} + exit_{rst}}{2 \cdot stock_{rst}}$$

Table 3 shows a summary of the variables used for the regression analysis.

Table 3: Summary of regression variables

Variables	Units	Description
Productivity	log	Measured as labour productivity.
Entry Rate	log	Total number of entrants in a two-digit nace industry and labour market region divided by the stock of existing companies in the same labour market region and industry.
Exit Rate	log	Total number of exitors in a two-digit nace industry and labour market region divided by the stock of existing companies in the same labour market region and industry.
Turbulence	log	Sum of entrants and exitors divided by 2* stock of existing firms.
Churning	log	Same as turbulence but controlled for changes in firm dynamics. (explained in detail below.)
Age	log	Number of years since the firm entered the market.
Export	1/0	Dummy variable that equals one once a firm exports.
R&D	log	Research and development expenditure of each firm.

5.1.2 Methodology

We employ the following reduced form regression analysis:

$$\phi_{irst} = \beta_0 + \beta_2 I_{rs,t-\tau} + \beta_5 X_{irst} + \alpha_i + \delta_t + \epsilon_{irst}$$

where ϕ_{irst} denotes labour productivity of a firm i active in region r and sector s at time t. $I_{rs,t-\tau}$ with the lags $\tau = \{1, 4\}$, collects the above presented compound measures of either the entry rate, churning rate or turbulence rate, measured for a given region and sector. X_{irst} represent firm characteristics such as age, export status, and R&D expenditure. We run six regressions, each including one of the three compound measures, for two different lags. Further, α_i and δ_t denote unobserved individual and temporal effects, potentially correlated with the explanatory variables, i.e. $E(\alpha_i | I_{rs,t-\tau}, X_{irst}) = E(\delta_t | I_{rs,t-\tau}, X_{irst}) \neq 0$. To account for α_i and δ_t in our regression analysis, we rely on two-ways within regression techniques (Wooldridge; 2010).We suppose that the idiosyncratic error term ϵ_{irst} is mean independent, i.e. $E(\epsilon_{irst} | I_{rs,t-\tau}, X_{irst}) = 0$.

Our parameter of interest is β_2, measuring the average effect of the different compound measures on firms' labour productivity.

Empirical results are presented in the next section with baseline estimates being depicted in Table 4. Note that our regression framework does not allow for interpretation of the parameters as causal effects, but should be understood as a statistical relationship between the explanatory and depend variables.

5.2 Results

5.2.1 Baseline Results

Table 4 shows our main regression specifications. The first three columns employ one-year lags in our main explanatory variables for industry dynamics while the last three regressions employ 4-year moving averages. All specifications use firm-level controls and both firm- and year fixed-effects. Standard errors are clustered at the industry- and region-level.

We observe that a significant fraction of variation in labour productivity is associated with key firm characteristics such as age, R&D and export activity; the coefficients for these variables are almost identical across specifications.

None of the specifications using 1-year lags for the compound variables in industry dynamics show statistically significant coefficients. Thus, a short term relation between firm dynamics and incumbent productivity is not reflected by our findings. As soon as we allow for longer time spans, using 4-year rolling averages of industry dynamics indicators, coefficients turn statistically significant and positive.

Table 4: Baseline Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
	1 year lag	1 year lag	1 year lag	4 year average	4 year average	4 year average
entry rate	0.00209					
	(0.00768)					
churning rate		0.00632				
		(0.00908)				
turbulence rate			0.00885			
			(0.0107)			
4 year entry rate				0.0365**		
				(0.0141)		
4 year churning rate					0.0269**	
					(0.0114)	
4 year turbulence rate						0.0572***
						(0.0159)
age	0.472***	0.436***	0.472***	0.473***	0.473***	0.473***
	(0.0760)	(0.0747)	(0.0760)	(0.0758)	(0.0760)	(0.0759)
r&d	0.00269***	0.00280***	0.00269***	0.00268***	0.00267***	0.00267***
	(0.000829)	(0.000743)	(0.000828)	(0.000829)	(0.000830)	(0.000828)
export	0.113***	0.112***	0.113***	0.114***	0.113***	0.114***
	(0.0187)	(0.0185)	(0.0187)	(0.0187)	(0.0187)	(0.0187)
Constant	10.05***	10.15***	10.07***	10.15***	10.13***	10.14***
	(0.196)	(0.194)	(0.192)	(0.196)	(0.185)	(0.190)
Observations	63,637	67,373	63,637	63,637	63,637	63,637
Adjusted R-squared	0.80	0.81	0.80	0.80	0.80	0.80
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In terms of coefficient magnitude, a 1% increase in churning rate (turbulence rate) is associated with a 2.7% (5.7%) increase in labour productivity. The effect of entry rates alone lies in between both values with 3.6%. The churning rate displays how productivity dynamics are associated with mere replacement of closures by new establishments. The higher the churning rate, the higher the share of entrants who are "mirrored" by firm exits. The turbulence rate, in contrast, reflects variation in productivity that is associated with the overall effect of entry and exit.

Looking at the construction of the industry dynamics variables in section 4.1, we see that turbulence and churning are analogously calculated with the exception that churning excludes effects of changes in firm stock, i.e. the absolute value of entry minus exit. Keeping that in mind and knowing that the difference in coefficients of churning and turbulence rate are statistically significant at the 5% level, we venture the following interpretation: Even if we do not know whether a 2.6% increase in productivity through mere replacement of firms is small or whether a 5.6% increase through turbulence is large, the proportion of both tells us that productivity dynamics is substantially associated with overall business dynamics. Only a smaller portion of this dynamics can be explained by mere replacement of firms and an at least equally large part of it can be associated to changes in firm stock.[5]

Changes in firm stock in an industry are nothing else than what is commonly referred to as structural change. So is productivity driven by structural change? We will not be able to answer this question because our model lacks the necessary exclusion restriction to allow for a causal interpretation of the

[5] The difference in coefficients of the four year churning and turbulence rates is significant at the 5% level. (p=0.017)

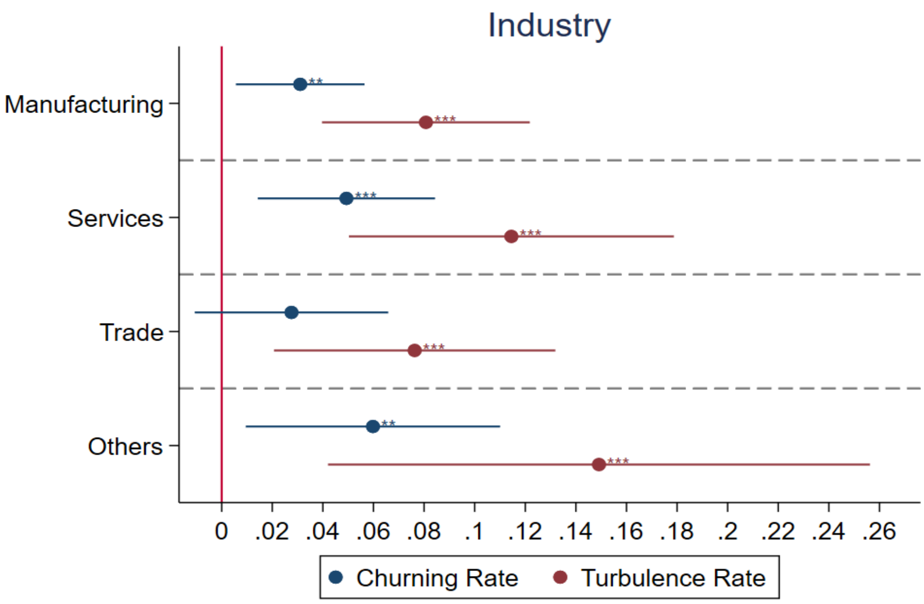
coefficients but results indicate that creative destruction is not only a process where old ideas are replaced by new ones but where new ones take over.

While we believe that this result alone is worth further investigation, we briefly allow for heterogeneity in terms of the sector of the incumbent firm as well as the technological degree in the next section, i.e. R&D intensity of its business model.

5.2.2 Sectoral Differentiation

In order to differentiate between sectors and technology, we run the regression specifications IV to VI from Table 4 and interact the industry dynamics indicators with sector and technology dummies. The results of both regressions are shown in Figure 11 and Figure 12. Sectors are broadly classified; where the classification is relatively broad and in line with the definition in section 3 of this report.

Figure 11: Regression coefficients and confidence intervals for interactions with sector dummies.



Note: Point Estimates and 95% Confidence Intervalls. * p < .1, ** p < .05, *** p < .01

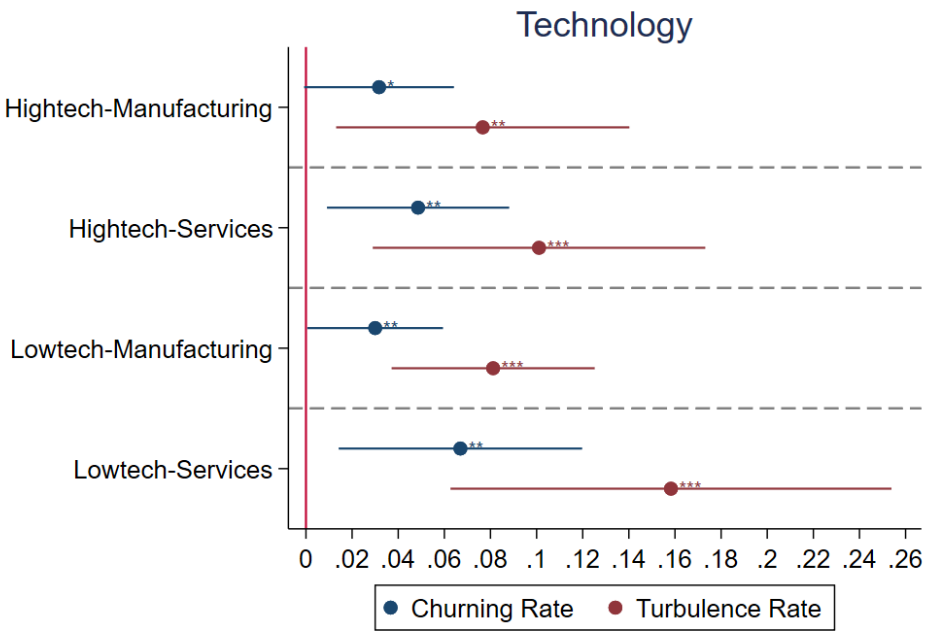
Figure 11 shows the regression coefficients of the compound variables and their 95% confidence intervals differentiated by sectors. Across all sectors, i.e. manufacturing, services, trade, and others, we observe a higher coefficient for turbulence than churning rates. This difference in coefficients is significant for the manufacturing, trade and service sectors (p-values of the t-test are: $p=0.0186$; $p=0.0849$ and $p=0.0467$ respectively). For "others", which is a conglomerate of all remaining firms that could not be allocated to the other industry classifications, we do not observe a significant difference in coefficients between churning rate and turbulence rate ($p=0.1002$). Thus, for firms that operate in manufacturing, trade and service industries, structural change beyond the replacement of exiting firms, acts as a significant driver of incumbent firms' productivity development.

5.2.3 Technological Differentiation

In the last subsection, we concluded that the main sectors of the economy do not show major differences in the relationship between replacement and turbulence with productivity dynamics. Across manufacturing, services and trade, productivity dynamics are associated with overall business turbulence by a larger part than by mere replacement of existing firm, i.e. structural change seems to be a driving force behind productivity development in all major sectors of the economy. However, when we differentiate between degrees of technology usage, we draw a different conclusion.

We split the sample in four sections: High- and lowtech manufacturing as well as high- and lowtech services. We differentiate between high- and lowtech industries by dividing industries into groups according to their R&D intensity.

Figure 12: Regression coefficients and confidence intervals for interactions with technology dummies.



Note: Point Estimates and 95% Confidence Intervalls. * p < .1, ** p < .05, *** p < .01

The classification is made following the definition of R&D-intensive industries in Gehrke et al. (2013) where e.g. high-tech manufacturing sectors are defined as 4- and 5-digit nace-codes with an average industry-R&D-intensity above 2.5%.

Across all technology groups, we find a higher coefficient for turbulence than for churning rates. The difference in coefficients is significant at the 5% level only in the case of lowtech manufacturing (p-value of t-statistic: 0.0238) and at the 1% level for lowtech services (p-value of t-statistic: 0.0608). For hightech manufacturing and hightech services, we do not find a significant difference between the coefficients of churning and turbulence rates (p=0.1612 and p=0.1499 respectively).

5.3 Discussion

Comparing the regression results differentiated by sectors and technology from the previous section shows that the effect of industry dynamics (beyond replacement) on incumbent firm productivity is strongest for lowtech industries in the manufacturing and service sectors. For hightech industries, replacing exiting firms by new entrants accounts as the main factor for changes in incumbent firm productivity. Additional competitive pressure introduced through changes in firm stock is not significantly associated with changes in incumbent firm productivity for hightech firms.

These findings lead us to the conclusion that the impact of firm dynamics on incumbent firm productivity is rather differentiated by technology adoption than industries. For hightech firms, the mere replacement of exiting firms suffices as driver for productivity of incumbent firms; structural change through additional firm dynamics beyond replacement does not significantly impact incumbent firm productivity. For lowtech firms, both components are significant drivers of incumbent firm productivity.

Our results are in line with the main notion of the seminal paper by Jorgenson et al. (2008). The authors evaluate the source of productivity growth for the US in the 1990s. At that time, the US experienced a fundamental shift towards information technologies that led economists predict a significant increase in productivity, which did not occur until the mid 1990s. This phenomenon was famously called the “computer productivity paradox” by Robert Solow (1987), which stated that information technologies aged everywhere but in the productivity statistics. Later on in the mid 1990s, the US experienced the expected increase in productivity. Jorgenson et al. (2008) attribute the sudden increase in productivity after the mid 1990s to rapid technological process in information technology producing industries (in the sense of Moore's law) and the subsequent diffusion of these technologies by non-technological industries. Advances in information technologies are captured by total factor productivity, since more output of computers, software and other information technology could be produced from a given set of inputs. This development eventually lead to a stark decrease in information technology prices. As a response, non information-technology firms purchased more information-technology products and substituted their capital stock towards higher quality goods. Thus, non information-technology firms diffused the technologies in their markets and increased productivity.

Translated to our setting, the relationship we find could indicate that since lowtech-sectors function rather as technology adaptors than drivers, these lowtech-sectors may be characterized by quite different competitive environments than hightech-sectors are. In hightech-sectors, IP rights and R&D capacity are the major drivers of competition. Innovative technologies challenge existing ones and make less-innovative firms exit the market, making room for more technologically advanced firms. On the contrary, in lowtech-sectors technology adoption gives rise to stronger competition because - other than in hightech-sectors - more firms even without IP-rights and R&D resources can participate in market competition. In such an environment, the mere replacement of firms does not drive productivity dynamics but instead, more firms than in hightech-sectors enter (and later exit) the market, resulting in fluctuations in firm stock which eventually drives productivity dynamics.

Summing up, our findings suggest that productivity dynamics is associated with business dynamics. While already mere business replacement is positively related with variation in productivity, structural change caused by variation in firm stock has an even stronger effect.

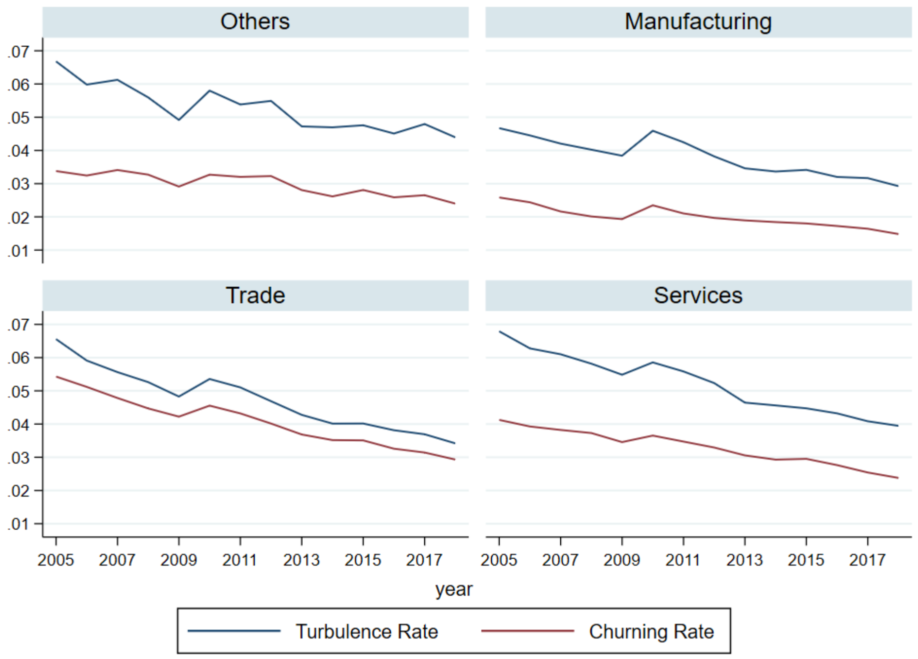
Not only in Germany have industry dynamics gone down substantially in the last 15 years.[6] This holds for both churning and turbulence rates as illustrated in Figure 12. Assuming for a moment that our results have a causal notion, then the strong decreases in business dynamics in the last years cannot be satisfactory for policy makers.

In such an environment of low business dynamics, it is questionable whether entering firms can put enough competitive pressure on incumbents to affect incumbent productivity growth in the longer run.

[6] See for instance De Monte (2021) for the French manufacturing sector.

Certainly, policy makers need to find ways to push business dynamics and eventually productivity growth. Furthermore, our results in 4.3 suggest that productivity growth does not only come from hightech sectors. Policy measures should also focus on the role of lowtech firms for productivity dynamics. Similarly to Jorgenson et al. (2008), our results suggest that not only high-tech but also lowtech sectors are key drivers of productivity. Jorgenson et al. (2008) point out that technology adaption is a driver of competition and productivity growth. We show that industry dynamics (namely entry, exit and changes in firm stock) represent another channel that relates to productivity development and technology diffusion.

Figure 13: Churning and Turbulence Rates in the German Economy from 2005 to 2019 by main sector



Source: Mannheim Enterprise Panel (ZEW), 2020 – Own Calculations.

6 Concluding Remarks

Declining productivity growth and decreasing business dynamics have raised fears of long-term negative impacts on economic growth in many industrialized countries. In this project, we show that there is cause for concern in Germany. Our analysis shows that both phenomena - i.e. low productivity and industrial dynamics - shape the development of the German economy since the mid 2000s. Not surprisingly, at least before the pandemic hit the world economy in 2020, these phenomena were on top of the political agenda of many decision makers. It is likely that after the pandemic industry and productivity dynamics will play even more important role since structural changes introduce new business opportunities. In this study we pile up different lines of empirical evidence that, taken together, suggest that productivity dynamics is largely driven by established incumbent players and generally likely to be slowing down in an environment of weak industrial dynamics.

Our analysis shows declining business dynamics in almost all regions and sectors with the notable exception of the IT-sector and the region of Berlin. Until 2011, the entry rate across industries was higher than the exit rate. Between 2011 and 2015, this relationship has reversed, such that more firms exited the market than entered. From 2015 on, we observe a stronger entry than exit rate again.

We find that aggregate productivity growth is always positive but slows down considerably over time. Furthermore, we measure a higher contribution to aggregate labour productivity growth of incumbents compared to entrants and exitors, where incumbents contribute most through within-firm productivity improvements related to learning effects. We also measure a substantial degree of allocative inefficiency, where labour shares shift from more to less productive firms, which hampers higher productivity growth.

Using three different compound measures for industry dynamics, we find that industry dynamics is significantly associated with productivity dynamics especially for lowtech sectors. For lowtech manufacturing and services, we find that industry dynamics beyond replacement of exiting firms significantly affects the development of incumbent firm productivity.

Our results suggest that finding ways to foster business dynamics will likely help to mitigate the weak productivity development. However, our empirical evidence on the relationship between industry dynamics and productivity gives rise to the question whether entrepreneurship policy has potentially focused too much on hightech-sectors in recent years. Following the argument of the seminal paper by Jorgenson et al. (2008) our results suggest that lowtech-sectors are key drivers of productivity. We find that total business turbulence is the major driver of productivity development in lowtech sectors and substantially exceeds the effect of mere replacement of firms: a finding which cannot be confirmed for hightech sectors. Lowtech firms compete by adapting technology while being less able to deter competition with IP or R&D capacities.

Jorgenson et al. (2008) suggest that this technology adaption is a driver of competition and therefore of productivity growth. In order to foster industrial dynamics, policy makers should therefore extent their focus to lowtech firms, too. In their setting, Jorgenson et al. (2008) show that information technology diffusion was the major driver of US productivity growth in the 1990s. Today, digitalization and decarbonization constitute similar technological challenges. While it is clear that the technological frontier of these technologies is not reached yet, enabling across- and within-industry adaption and diffusion of these technologies will potentially be equally important in fostering business dynamics and productivity growth.

The basic mechanism hightlighted by Jorgenson et al. (2008) also sheds light on the challenges for business turnover during and following the structural crises caused by the pandemic. During its first phase massive government support slowed down firm exit with non-viable business models. Such businesses still consumed resources which led to a situation where valuable resources were stuck in those business models. In addition, such business models might compete using government support while young firms have limited support by governments. This drives down industrial dynamics. An important challenge for the post pandemic world is to revitalise entry rates and stimulate technology adaption and adoption of new business models as a base to restore or even more to increase productivity growth beyond the level before the crisis.

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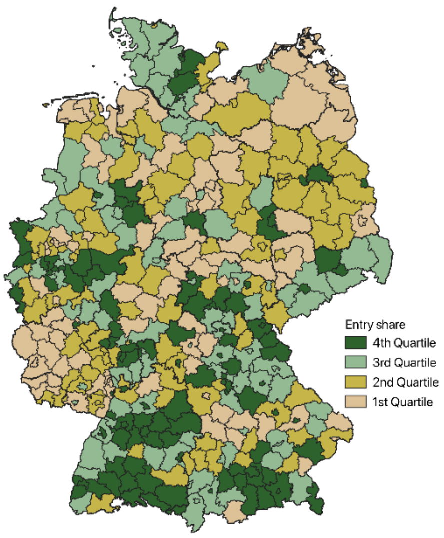
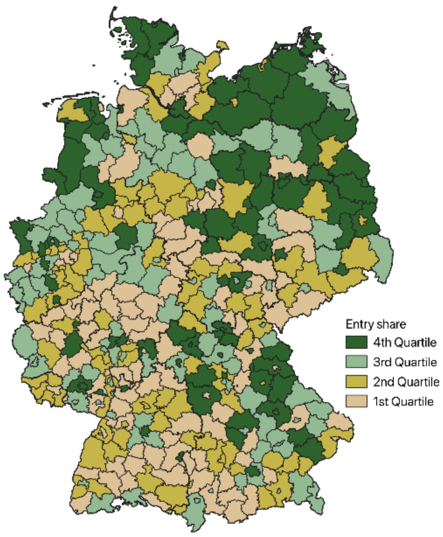
8 Appendix A: Maps on the Sector Level

In this Appendix, all maps to the left represent entry/exit rates weighted by the total amount of eligible working population in the respective district. The right maps represent entry/exit rates weighted by the total amount of firms in the respective district.

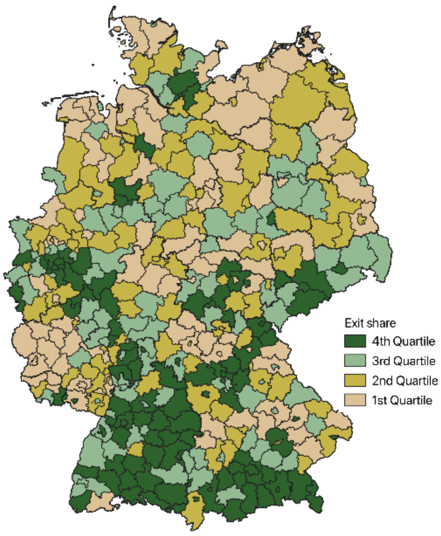
1.1 Hightech Manufacturing

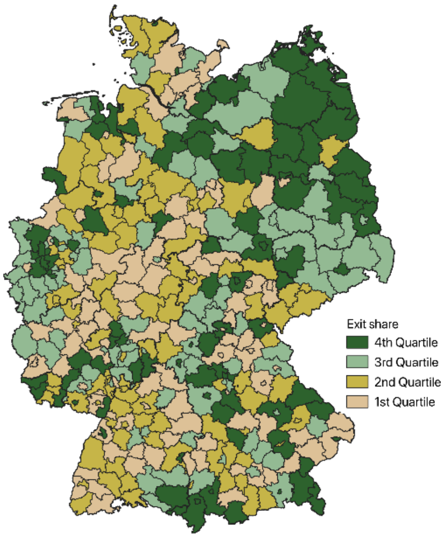
Entry Rates :





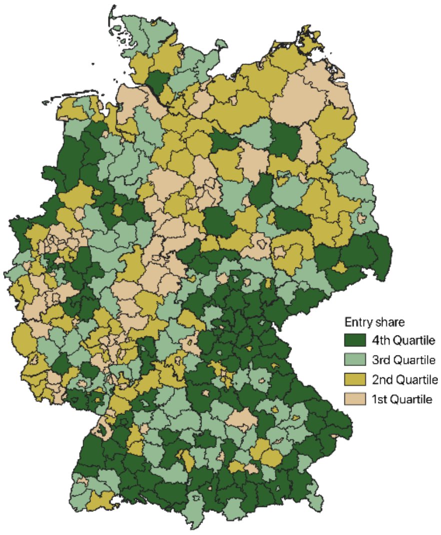
Exit Rates:

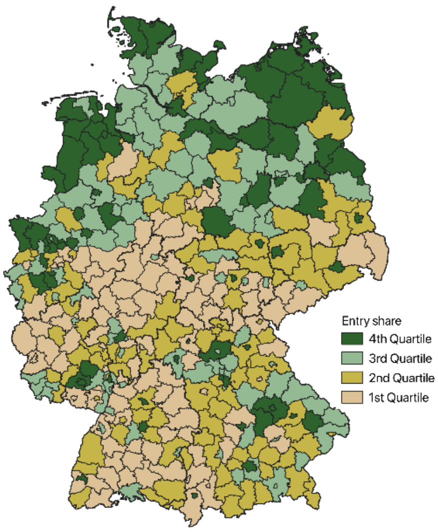




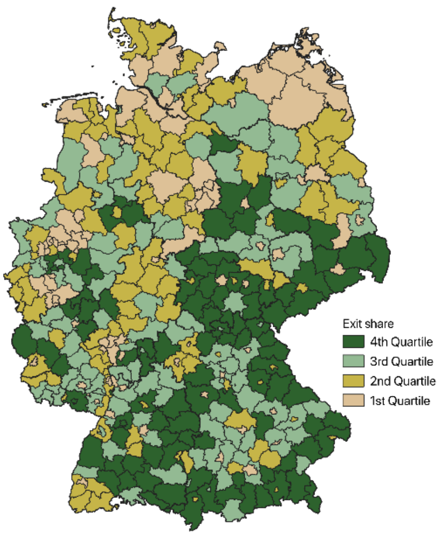
1.2 Lowtech Manufacturing

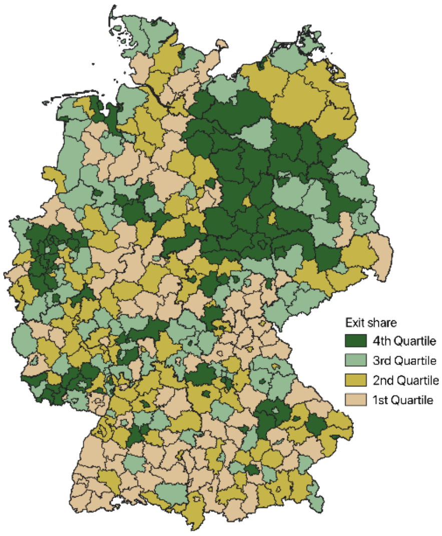
Entry Rates:





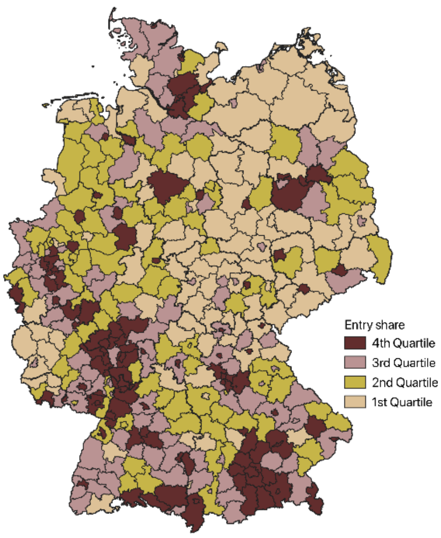
Exit Rates:

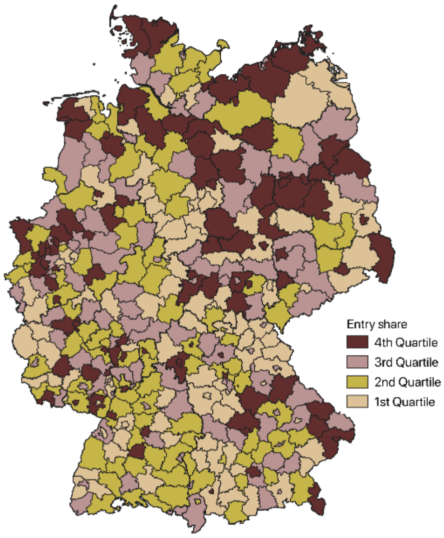




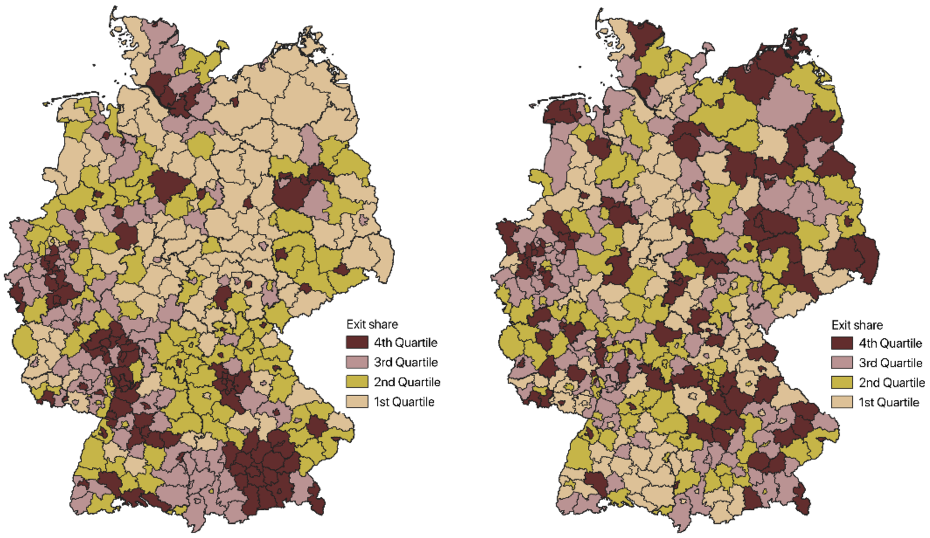
1.3 Software

Entry Rates:





Exit Rates:


Exit share
4th Quartile
3rd Quartile
2nd Quartile
1st Quartile
Exit share
4th Quartile
3rd Quartile
2nd Quartile
1st Quartile

Appendix B: Regression Tables

9.1. Industry Interactions

	(1)	(2)	(3)
	OLS	OLS	OLS
	4 year average	4 year average	4 year average
VARIABLES	l_prod_head	l_prod_head	l_prod_head
others#entry	-0.175		
	(0.782)		
manufacturing#entry rate	0.771**		
	(0.325)		
trade#entry rate	1.578***		
	(0.550)		
services#entry rate	0.607**		
	(0.302)		
others#churning rate		0.0598**	
		(0.0251)	
manufacturing#churning rate		0.0310**	
		(0.0127)	
trade#churning rate		0.0276	
		(0.0191)	
services#churning rate		0.0493***	
		(0.0175)	
others#turbulence rate			0.149***
			(0.0534)
manufacturing#turbulence rate			0.0807***
			(0.0205)
trade#turbulence rate			0.0763***
			(0.0277)
services#turbulence rate			0.115***
			(0.0320)
age	0.916***	0.944***	0.945***
	(0.121)	(0.127)	(0.127)
r&d	0.0104***	0.0110***	0.0110***
	(0.00377)	(0.00399)	(0.00399)
export	0.556***	0.565***	0.566***

	(0.0826)	(0.0883)	(0.0882)
Constant	8.502***	8.616***	8.645***
	(0.336)	(0.329)	(0.332)
Observations	89,433	83,377	83,367
Adjusted R-squared	0.684	0.678	0.678
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

9.2. Technology Interactions

	(1)	(2)	(3)
	OLS	OLS	OLS
VARIABLES	l_prod_head	l_prod_head	l_prod_head
hightechn manufacturng#entry rate	0.973		
	(0.835)		
hightech services#entry rate	0.692		
	(0.689)		
lowtech manufacturing#entry rate	0.892***		
	(0.312)		
lowtech services#entry rate	0.658**		
	(0.295)		
hightech manufacturing#churning rate		0.0317*	
		(0.0161)	
hightech services#churning rate		0.0486**	
		(0.0196)	
lowtech manufacturing#churning rate		0.0300**	
		(0.0146)	
lowtech services#churning rate		0.0670**	
		(0.0262)	
hightech manufacturing#turbulence rate			0.0767**
			(0.0316)

hightech services#turbulence rate			0.101***
			(0.0358)
lowtech manufacturing#turbulence rate			0.0812***
			(0.0219)
lowtech services#turbulence rate			0.158***
			(0.0475)
age	0.939***	0.964***	0.966***
	(0.128)	(0.134)	(0.134)
r&d	0.0105**	0.0111**	0.0111**
	(0.00408)	(0.00430)	(0.00430)
export	0.571***	0.579***	0.579***
	(0.0885)	(0.0949)	(0.0948)
Constant	8.387***	8.528***	8.554***
	(0.350)	(0.340)	(0.341)
Observations	79,898	74,645	74,635
Adjusted R-squared	0.660	0.652	0.653
Year FE	YES	YES	YES
Firm FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C: Additional Descriptive Statistics

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment (headcount)	288164	323.889	3489.819	0	475000
Revenue	191019	1610.96	16676.806	0	2700000
Age	296425	25.962	35.124	0	683
Export	159890	.414	.493	0	1
R&D	168295	39.119	807.369	0	67357.195
Churning Rate (4 year)	284979	.031	.022	0	5
Churning Rate	231142	-3.546	.553	-6.217	.693
Turbulence Rate	296310	.044	.034	0	2
Turbulence Rate (4 year)	296310	.172	.098	0	8.5
Entry Rate	296310	.054	.049	0	3
Entry Rate (4 year)	284979	.057	.042	0	7

Note: Monetary Values in 100.000 Euro.

Pairwise correlations

Variables	Productivity	Entry Rate	Exit Rate	Churning	Turbulence	Age	Export	R&D
Productivity	1.000							
Entry Rate	0.001	1.000						
Exit Rate	-0.001	0.110	1.000					
Churning Rate	-0.001	0.444	0.507	1.000				
Turbulence Rate	0.000	0.800	0.685	0.632	1.000			
Age	-0.002	-0.030	-0.024	-0.082	-0.037	1.000		
Export	0.005	-0.118	-0.009	-0.104	-0.092	0.163	1.000	
R&D	0.001	-0.006	-0.005	-0.010	-0.007	0.083	0.065	1.000

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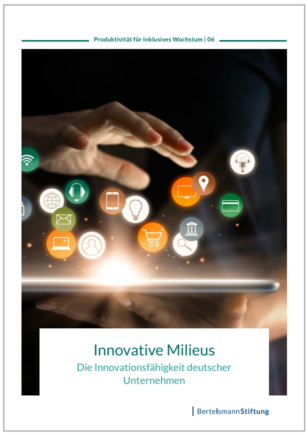

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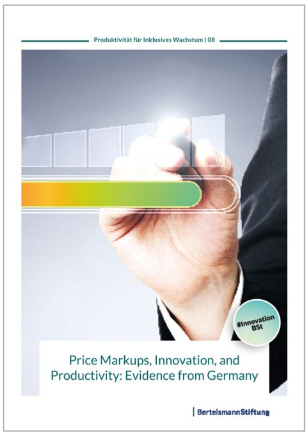

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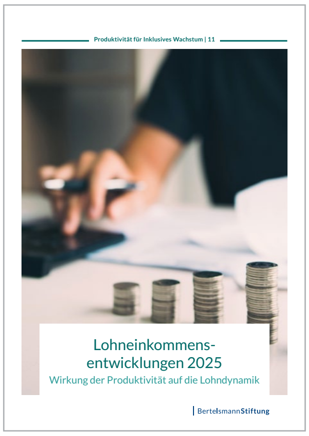

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