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Abstract

We analyze the effect of labor mobility and innovation on productivity growth. With event-study analysis based on exogenous worker deaths and shift-share international trade shocks, we show that both the extent and direction of worker mobility affect firm productivity. We develop a multi-worker-firm framework with random search and on-the-job mobility to estimate the relative contribution of mobility and R&D to growth. Estimated on a balanced growth path using Swedish microeconomic data, we find that over 70% of output growth can be attributed to worker mobility. Our results suggest that a slowdown of worker mobility can depress aggregate economic growth.

JEL codes: J24, J41, J63, J64
Keywords: Productivity, Worker Mobility, Innovation

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1 Introduction

Approximately one fifth of all jobs in the US economy are either created or destroyed each year (Davis and Haltiwanger, 1992; Leonard, 1986). This worker mobility redistributes not only productive working hours but also workers' knowledge and ideas across firms and sectors of the economy. Worker mobility differs from firms' internal efforts at idea creation in two main aspects. Unlike research and development (R&D), the benefits of worker knowledge and ideas are not exclusive to the firm beyond the duration of the employment match. Moreover, in contrast to R&D — which tends to be concentrated among a few firms, with a considerable fraction of firms reporting no R&D activities at all (Klette and Kortum, 2004) — labor mobility is pervasive throughout the economy. In fact, all firms are potential beneficiaries of this source of new ideas. These distinctions indicate that labor mobility and R&D can mutually reinforce one another at the macroeconomic level: while R&D and worker mobility may serve as substitutes at the firm level, they complement each other at the aggregate level of the economy. Consequently, worker mobility has the potential to amplify economic growth.

In this paper, we quantify the role of workers in driving economic growth in the economy. We make two main contributions. First, we provide empirical evidence of the effect of scope and direction of worker mobility on firm productivity, leveraging highly granular register data for Sweden on firms, products and workers. We consider both horizontal productivity changes, such as increases in output per worker, as well as vertical productivity changes such as adoption of new products. Our data's granularity allows us to consider arguably exogenous shifters to tease out the effect of worker mobility. Second, we develop a theoretical framework that enables us to disentangle the contributions to economic growth arising from labor mobility and firm-generated innovation. We construct a novel multi-worker-firm environment with on-the-job search. This framework is distinctive in its allowance for the interplay of heterogeneous worker and firm productivity while remaining sufficiently parsimonious to ensure the tractability of the model. We show that in our model, we can separate the effect of firm size and productivity on joint firm surplus, allowing us to define a balanced growth path with closed-form solution. In technical terms, we show that the joint firm surplus is affine in firm size, such that even despite the multi-worker-firm environment, the analysis on the balanced growth path of productivity is reminiscent of the analysis in Lucas and Moll (2014) that does not feature firms. Our model conceptualizes firms as productive communities with shared histories, shaped by learning and innovation events as well as worker mobility. This approach allows us to interpret knowledge diffusion as the result of intra-firm learning driven by labor mobility, facilitating a closer alignment between model elements and empirical data. It also enables us to distinguish between different sources of ideas, in the

form of mobility and innovation. Our model stands out in allowing for job-to-job mobility, an arguably salient factor in worker mobility patterns but that is notoriously difficult to capture in multi-worker-firm environments. We show that there exists an equilibrium where firm surplus is affine in firm size with or without job-to-job mobility, thereby allowing us to flexibly extend our model to include this case. To discipline the model, we draw on comprehensive data from the Swedish manufacturing sector, where innovation has a more pronounced influence compared to other economic sectors. Our findings emphasize the central role of worker mobility in driving economic growth. We find that worker mobility accounts for over 70% of aggregate growth in the manufacturing sector. Intuitively, our results vary significantly with the prevalence of on-the-job search. In a split-sample analysis of the last two decades, we find that the contribution of worker mobility has slightly decreased, coinciding with a reduction in worker mobility and an increase in R&D intensity.

Our findings support the idea that worker mobility as well as R&D are both significant forces in driving aggregate productivity growth. At a first glance of the data, we find that sectors with more worker mobility and those who tend to hire more often from more productive firms see higher aggregate productivity growth. We then leverage quasi-experimental variation to argue for a causal interpretation to these data patterns. First, we exploit exogenous trade demand shocks to local peer firms to analyze the effect of shifts in the distribution of newly hired workers on local firm productivity. Second, we build on a literature that exploits sudden and unexpected worker deaths to examine the effect of the loss of worker-embodied knowledge on firm product expansion. Our empirical evidence thus covers both worker arrival as well as worker separations. As negative trade shocks reallocate workers from one firm to another, we observe arguably exogeneous variation in likely sending firms. We find that it matters which firm is hit by such shocks: if above median productivity firms are exposed to negative demand shocks, local competitors see increases in labor productivity on impact, whereas this is not true when a lower quality firm is hit. This evidence adds to the previous literature on local effects of trade-based demand shocks, by showing that labor market spillovers can have heterogeneous effects depending on the origin firms. Cautious of possible worker-selection effects, we find that our results also hold when controlling for worker quality. Finally, leveraging sudden and unexpected worker separations due to worker death, we estimate a negative effect of worker disappearance on the likelihood of product entry, especially for those workers with relevant previous work experience. This evidence complements previous insights on disappearing workers that has mostly focused on the loss of match-specific productivity whereas we focus on general knowledge by showing that

transferable product-knowledge affects future product expansion.[1]

In our theoretical framework, we follow these insights by describing workers as vessels of knowledge. Firms generate new ideas through R&D and transmit these ideas to their workers, thereby assuming the dual role of innovators and knowledge transmitters. In our model, a multi-worker-firm environment with constant returns ensures that workers are willing to move to more but also to less productivity firms, as their superior knowledge benefits outside firms with lower productivity more than their previous firms. This is a crucial feature such that firms can benefit from other firms' knowledge through on the job search without having to wait for a highly knowledgeable worker to enter the pool of unemployed workers. Hence, whereas in frameworks lacking job-to-job mobility but incorporating knowledge transfers, unemployment aids in reallocating knowledge across the economy — resulting in an unpleasant trade-off between knowledge diffusion and inactivity — in our model, this trade-off is resolved. Through this mechanism, our model captures a significant and quantitatively important aspect of worker mobility, namely downward worker mobility (see, for instance, Sorkin, 2018), which can otherwise only be rationalized through the presence of compensating differentials (such as amenities or future wage growth). The worker-search setup allows for embedding in a standard balanced growth setting. We demonstrate that there exist closed-form equations describing growth in the economy and illustrate how it relates to its various drivers. Finally, we leverage empirical insights on the effect of worker departures and worker arrivals for calibration. In a variance decomposition, we show that our theoretical results on the importance of worker mobility for growth are quantitatively comparable to empirical estimates. Our analysis provides empirical and theoretical support for the proposition that labor market frictions, by constraining labor mobility, impose substantial economic costs on the broader economy. In the light of decreasing average worker mobility, our analysis suggests a simultaneous decrease in aggregate productivity growth.

The paper relates mainly to three strands of the literature. The first strand has empirically analyzed the effect of workers' mobility and firm outcomes, either by considering special workers within the firm such as engineers broadly defined (Harrigan et al., 2023; Tambe and Hitt, 2014), CEOs or managers (Meinen et al., 2022; Bennedsen et al., 2020; Jones and Olken, 2005; Becker and Hvide, 2021; Mion and Opromolla, 2014), inventors (Jaravel et al., 2018; Almeida and Kogut, 1999; Singh and Agrawal, 2011; Jaffe et al., 1993; Kaiser et al., 2015;

[1]Worker movements among top tech firms and their anecdotal press coverage are real-world examples of worker mobility events spurring general knowledge transfer. For instance, Vox wrote in 2016 "New Apple hire is probably a sign that 'Tesla's graveyard' will eventually be a threat to Tesla" (Source). Another news outline summarized a trajectory as "Ex-Tesla VP turned Apple Car engineer poached by electric plane startup in latest staff loss" (Source).

Braunerhjelm et al., 2020) or workers more broadly (Hoey et al., 2023; Stoyanov and Zubanov, 2012, Serafinelli, 2019). Hatzigeorgiou and Lodefalk (2019) and Parsons and Vézina (2018) detect an effect of immigrants on the likelihood that firms export to the origin countries of the immigrants. Some other studies have used exogeneous worker disappearances through death for identification and estimation (Andersen and Nielsen, 2011; Bertheau et al., 2022; Jäger and Heining, 2019; Bloesch et al., 2022; Sauvagnat and Schivardi, 2023). While existing literature has examined different facets of innovation and worker mobility, our contribution lies in analyzing the direction of worker mobility causally. While Stoyanov and Zubanov (2012) analyze the effect of hiring from more productive firms, we extend their analysis by leveraging exogenous mobility shifts, allowing us to address potential endogeneity concerns. To our knowledge, we are the first to utilize sudden and unexpected worker deaths to discern how attributes of past employers influence the productivity of receiving firms. Additionally, we pioneer the exploration of whether a worker's prior experience in the production of a specific product influences the likelihood that the receiving firm will initiate production of the same product. Thus, our study contributes by providing well-identified evidence that underscores the significance of workers in the dissemination of knowledge across firms.

The second strand of the literature has advanced on the theoretical study of either multi-worker firms or models of idea diffusion with balanced growth paths. Our paper is closely related to Bilal et al. (2022), Engbom (2023), Audoly (2023) and Bilal et al. (2021), yet introduces worker heterogeneity and allows some simplifications compared to their setups. It shares with Jarosch et al. (2021) the focus on learning in firms, but does not consider wage formation, similar to Bilal et al. (2022). In addition, we use exogenous variations in the data to estimate key model parameters. Thematically, the paper is related to Lentz and Mortensen (2022), yet does not feature a product quality ladder and focuses on a balanced growth path. The paper also relates to Lucas and Moll (2014), Perla and Tonetti (2014), Kortum (1997), Luttmer (2007), Benhabib et al. (2021), Buera and Oberfield (2020), Koenig et al. (2016), Hopenhayn et al. (2020) and Bradley and Gottfries (2022) through its analysis of a balanced growth path in an economy with knowledge diffusion. While these papers mostly abstract from the mechanism behind idea diffusion, we explicitly bring to the model both internal firm innovation as well as frictional labor mobility and associated idea transmission. In this sense, the paper is close to Akcigit et al. (2016), who also use micro-data to discipline a model of diffusion of ideas, however in the area of patents. The paper is related to a complementary paper on the role of knowledge diffusion on a balanced growth path with non-compete contracts, Liu (2023). Differently from this paper, we analyze multi-worker-firms. Due to this focus, we can establish closed form expressions for the balanced growth path in all cases, whereas Liu (2023) can only do so when restricting to a perturbation of equilibrium

worker mobility.

The third strand of the literature discusses the relationship between worker reallocation and productivity as mediated through employment protection legislation (EPL) and notably firing costs. In this literature, EPL are found to depress productivity and employment (Hopenhayn and Rogerson, 1993; Da-Rocha et al., 2019; Bartelsman et al., 2016, Aghion et al., 2023) and productivity growth (Poschke, 2009) as well as shift the type of innovation in the economy (Mukoyama and Osotimehin, 2019). As EPL equally depresses labor mobility, this literature predicts a positive relationship between worker reallocation and productivity across countries. Differently from this literature, we discuss a relationship between worker mobility and innovation for a fixed EPL as mediated through worker mobility and imitation.

The paper proceeds as follows. In section 2 we outline our data sources and section 3 provides empirical results on the importance of worker mobility for firm growth. Motivated by the presented evidence, we describe a theoretical framework and derive a balanced growth path of the economy in section 4. In section 5 we show results for the decomposition of economic growth in the economy. Section 6 concludes.

2 Data

In the following, we outline our data sources in section 2.1 and discuss our sample in section 2.2. We then provide a first glance at the data by showcasing aggregate correlations across worker mobility, productivity growth and innovation in section 2.3.

2.1 Data Sources

We leverage four main Swedish data sources: a firm level data set, a worker level dataset, a product-level data set, and the death registry. The set of variables used per dataset, together with the period covered, is summarized in Appendix Table A.1.

The firm-level data derives from the database called *Företagsdatabasen* and includes for example value added, total wage sum and other production costs. The dataset is based on information from the Swedish Tax Authority on administrative registries of the firms' balance sheets.

The worker-level data is called the *Swedish Longitudinal Integrated Database for Health Insurance and Labour Market Studies (LISA)*. It contains information on all Swedish workers

in the private sector, and has previously been used for example by Balke and Lamadon (2022) and Saez et al. (2019). It includes information such as income, education, and age. Occupations are reported according to the Swedish Standard Classification of Occupations (SSYK).[2] We can link employers and employees using firm identifiers and therefore track workers' experience based on the firm they work at. The reliability and quality of this data is regarded as very high, since it is based on tax reports by firms and misreporting is punishable by law.

The product-level data is drawn from the dataset *Industrins Varuproduktion (IVP)*, which is based on surveys on the production of Swedish manufacturing firms, and has previously been used by Carlsson and Skans (2012). The dataset includes all firms with at least five employees, and contains information on what products they produce up to the 8-digit Combined Nomenclature (CN) level.[3] For each year, firms report both quantity and price for each product. Using the worker-level data, this product-level data allows us to track workers' experience in specific lines of production.

We also utilise data from the dataset *Research and Development in the private sector* to obtain data on the expenditure of firms on R&D. We specifically use the overall amount in Swedish kronor that firms spend on R&D. The basic criteria for distinguishing R&D from related activities are that there should be an element of innovation and creativity in the activity. The outcome of the activity should be uncertain, and the uncertainty should also apply to the expenditure of financial and human resources. However, the activity should be planned and budgeted and the outcome should be intended to be potentially transferable and replicable in other activities.

Finally, we also leverage information on worker deaths from the registry *Dödsorsaksregistret* which includes information on date and cause of death as classified through the International Classification of Disease ICD, version 10 (see Brooke et al., 2017, for an extensive description of the dataset). In the medical literature, a sudden and unexpected death (SUD) is defined "as a natural, unexpected fatal event that occurs within one hour of the beginning of symptoms in an apparently healthy subject or in one whose disease was not so severe that such an abrupt outcome could have been predicted" (Lim et al., 2010). We identify unexpected worker deaths using information on the cause of deaths from the registry, building on Andersen and Nielsen (2011). Similar to them, we consider the list of ICD-10 causes of death in Table 1 to identify

[2]The base for SSYK is the international standard classification of occupations with reference year 2008 (ISCO-08).

[3]The CN system is the EU classification scheme for products, and is used by custom offices as well as statistical agencies, similar to the US equivalent Harmonised System (HS).

ICD Code	Description
Natural Causes	
I22-I23	Acute myocardial infraction
I46	Cardiac arrest
I50	Congestive heart failure
I60-I69	Stroke
R95-R97	Sudden death by unknown cause
Unnatural Causes	
V00-V89	Traffic accidents
V90-99, X00-X59, X86-X90	Other accidents and violence

Table 1: ICD diagnosis of Death – Sudden unexpected death

sudden deaths. Among natural causes of death, we thus consider acute myocardial infarction (ICD-10: I22-I23), cardiac arrest (I46), congestive heart failure (I50), stroke (I60-I69) and sudden deaths by unknown causes (R95-R97). Among unnatural deaths, we consider traffic accidents (V00-V89) and deaths caused by other accidents and violence (V90-V99, X00-X59, and X86-X90) which excludes suicides or violent deaths due to relatives.

2.2 Sample

Our data covers the years 1997–2019. We restrict the population to workers 15–65 years of age with an observed occupation code, and to firms with at least five employees. Table 2 includes summary statistics for our data sample. Our data spans around 1.2 million unique workers working for around 25,000 firms. Workers are on average 43 years old. Around 31% of workers have a college degree and 1% hold a PhD. A worker is likely to leave the current employer with probability 17% each year. Our firm data shows that firms' labor productivity grows at around 2% per year on average. Moreover, the median firm is fairly small and employs around 12 workers. This means that exits of specific workers are likely to be fairly salient for these firms' operations. Around 7% of firms adopt a new product every year, and around 2% report positive R&D investments every year. This investment intensity is a small number, especially compared to the 17% of workers changing employment each period, as shown in Panel A. The mean age at death is 51, and is as expected higher than the sample average age. There are around 2,000 sudden death events in our matched sample where a firm experiences at least one death, out of the 242,380 firm-year observations in total, totalling about 1% of all matched observations. This means that death events are relatively rare, but more frequent than for example in the study by Sauvagnat and Schivardi (2023), who look at deaths of Italian CEOs (0.1%) and similar in magnitude to Bertheau et al. (2022) but

smaller than Jäger and Heining (2019).[4].

Table 2: Summary Statistics

	Obs. (1)	Mean (2)	SD. (3)	Median (4)	Min. (5)	Max. (6)
A) Workers						
Age	8,105,124	42.91	11.62	43.00	16.00	64.00
Female	8,105,124	0.24	0.43	0.00	0.00	1.00
Income	8,105,124	3,556.81	2,054.78	3,262.00	1.00	437,802.00
Less than HS	8,105,124	0.69	0.46	1.00	0.00	1.00
More than HS	8,105,124	0.31	0.46	0.00	0.00	1.00
Phd	8,105,124	0.01	0.08	0.00	0.00	1.00
Stayer	7,643,679	0.83	0.37	1.00	0.00	1.00
# Workers	1,168,308					
# Firms	21,508					
# Occ. Groups (4-Digits)	366					
B) Firms						
Y/L Growth Rate	212,932	0.02	0.34	0.03	–8.95	7.71
Firm Size	242,380	50.67	329.63	12.00	5.00	22,610.00
New Product Adoption	72,454	0.07	0.25	0.00	0.00	1.00
R&D dummy	242,380	0.02	0.15	0.00	0.00	1.00
# Firms	25,216					
# Prod. Codes (4-Digits)	236					
B) Deaths						
Age at Death	2,027	50.81	11.68	54.00	18.00	64.00
# Events	2,027					

2.3 Aggregate Data Patterns

For a first look at our data, we explore correlation patterns among worker mobility and productivity growth. Specifically, we examine whether both the extent of mobility due to worker-firm separations and the direction of worker mobility, as captured by the difference in quality between origin and destination firms, correlate with aggregate productivity growth at the sector level. We use two proxies for productivity growth: vertical productivity growth computed as the average growth of labor productivity, and horizontal productivity growth as captured through new product adoptions. After considering the correlation of mobility patterns with productivity growth, we examine the size of these effects by comparing them

[4]Note that Jäger and Heining (2019) do not observe the cause of death and hence start from a larger sample of disappearing workers. To focus on unexpected deaths, they discard workers who had been on sick leave in the five years prior to the death event.

to the correlation of productivity growth with R&D activity.[5]

To characterize worker mobility, we calculate two measures: one describing the extent of mobility and the second describing the direction of mobility. First, we compute the mean rate of worker separations at the four-digit sector level as a measure for the extent of mobility. We only include final separations where the worker never returns to the firm. Second, we calculate the per-sector share of firms who hire from a firm with a superior level of labor productivity to characterize the direction of mobility. We compute different averages by skill groups, leveraging occupation and income information for skill classification. Specifically, we rank all occupations according to the annual income of its workers and compute separation rates for the top decile and below median occupation groups separately. This classification mirrors the hypothesis that high income, high skill workers might have a higher knowledge level to impart. Consequently, we adopt a more comprehensive definition of skill than those used in previous studies, such as the focus on technology workers by Harrigan et al. (2023), the emphasis on IT workers by Tambe and Hitt (2014), the analysis of inventors' mobility by Jaravel et al. (2018), or the studies of entrepreneurs and managers by Becker and Hvide (2021) and Mion and Opromolla (2014), respectively.

Figure 1 showcases our results. In the left panel, we first see a scatter plot across sectors showing the level of labor productivity growth and separation rates. The size of the circles indicate the total value added in each sector. Blue colored circles indicate values for workers in below median wage occupations, and red colored circles pertain to workers in the top decile of occupations. We see that there appears to be a positive correlation between separation rates and productivity growth among the workers with the highest level of embodied knowledge, i.e. workers in the highest paid occupations (red color). Interestingly, the same pattern is weaker when one focuses on the below median occupations (blue color). In the left panel of Figure 2, we analyze instead how separation rates are correlated with horizontal productivity growth, i.e. the likelihood that firms in a sector enter production of a new eight-digit product line. Interestingly, a similar pattern emerges, where mobility of workers in the most knowledge-intensive occupations correlate positively with productivity growth (product expansion), while mobility by workers in the less knowledge-intensive occupations do not seem to be associated with this type of productivity dynamics. For the direction of mobility, the patterns are similar to those observed for separation rates. Hiring from firms with higher

[5]While we focus on cross-sectoral data for Sweden in this paper, a reader might wonder about the cross-country relationship of mobility rates and productivity growth. Using the cross-country data set from Donovan et al. (2023), we pursue this analysis in Appendix section B and show that across countries, higher entry rates to new employers are positively correlated with GDP growth per capita. This positive association is particularly strong in countries with lower GDP per capita.

levels of productivity appears to be associated with faster productivity growth, both for vertical (Figure 1) and horizontal (Figure 2) productivity growth. Both data patterns lead to statistically significant differences in correlation estimates across skill groups.[6]

Importance of mobility One way to assess the importance of these correlations is to relate them to similar estimates related to firms' effort on research and development (R&D). It is generally agreed upon that R&D efforts are quantitatively important for the evolution of firm productivity. In the following, we analyze the size of the correlation of productivity growth and R&D as compared to the correlation with worker mobility patterns. If the correlations with worker mobility are of similar magnitude and pertain despite controlling for the level of R&D, it would be suggestive evidence that worker mobility is an independent and significant factor in driving productivity growth. We implement this analysis by employing the same regression framework as in Online Appendix Tables A.2 and A.3, but where we also include dummies for whether firms engage in R&D, such that the sector average of this number denotes the share of firms conducting R&D. In order to be able to compare the effect of mobility with that of R&D, we first standardize our measures of mobility and R&D. We then regress our outcome variables in Figures 1 (mean labor productivity growth) and 2 (product expansion) on standardized separation rates and the standardized measure of R&D. Then we do the same exercise for the direction of mobility, using the standardized rate at which firms hire from a more productive firm.

We demonstrate our results in Table 3. Our conclusion is that in most specifications the links with separation rates and hiring rates are as important as the link to R&D. This is especially the case for the top decile of occupations, while for the bottom half of occupations the coefficient on R&D is usually of a higher magnitude than the one for mobility.

If the correlation between mobility and productivity growth is driven by knowledge transfer through workers, job-to-job moves should have a stronger link to productivity growth than moves involving unemployment. During unemployment, workers may lose or become

[6] In Online Appendix Tables A.2 and A.3 we perform regressions for the correlations depicted in the figures above. We report results for estimating the regression line using the bottom half of the occupations according to the income ranking, and using the top decile, respectively. Appendix Table A.2 reports the regression coefficient on labor productivity growth. Columns (1) and (2) show that the regression estimate is always larger for top decile occupations than for the bottom half. The differences between the estimators are statistically significant in the majority of cases. Appendix Table A.3 reports the results for product expansion and the same pattern applies. In columns (3) to (6) we add additional controls. Overall, we find that the patterns remain. In column (3) to (4), we control for labor productivity in the sector, in columns (5) and (6) we further control for sectoral volatility. We also include volatility in foreign demand in this pattern, based on a shift-share instrument using the baseline export patterns of firms and the subsequent changes in aggregate global exports to those destinations (see for example Hummels et al., 2014).

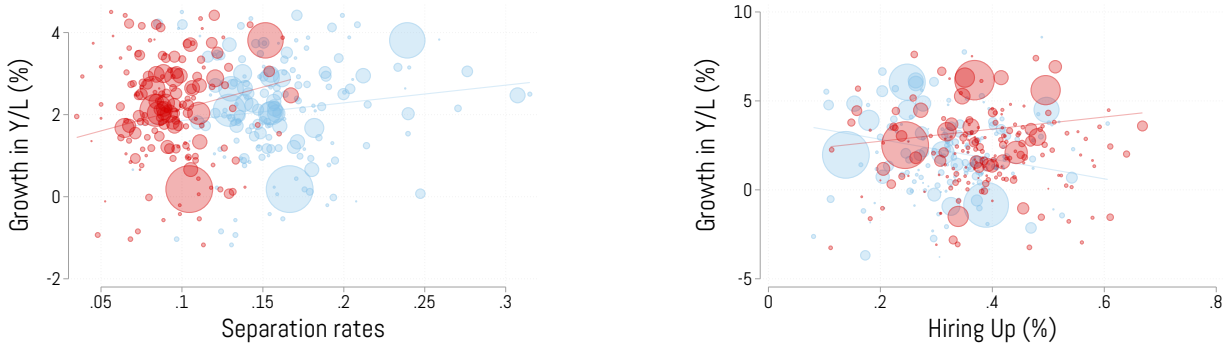


Figure 1: Vertical productivity growth: Growth in Y/L

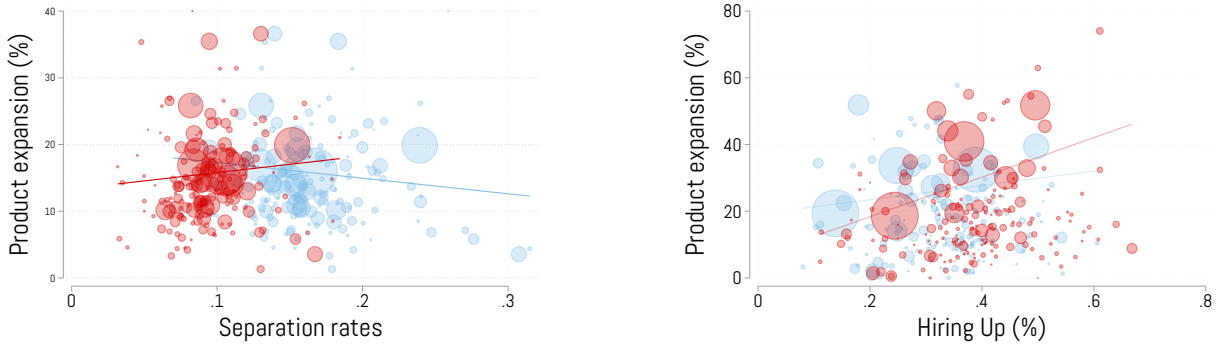


Figure 2: Horizontal productivity growth: Product expansion

Notes: Upper panel - The left column shows binned scatter plots of the separation rate and the growth in labor productivity for occupations with below median wages (blue) and top decile occupations (red). The right hand side shows the share of workers who last worked at higher-productivity firms before entering the current firm and the growth in labor productivity for these two types of workers. *Lower panel* - The left panel shows binned scatter plots of the separation rate and the likelihood of product expansion for all workers (blue) and top decile occupations as categorized by average earnings (red). The right hand side shows the share of workers who last worked at higher-productivity firms before entering the current firm and the likelihood of product expansion for these two types of workers. Ranking of firms is established in the year prior to mobility based on observed Y/L. A unit of observation is a 4-digit industry. Data for Sweden, 1997-2019.

Table 3: Growth in vertical and horizontal labor productivity with standardized mobility and R&D.

Dep. var.:	Growth in labor productivity		Product expansion	
	Bottom half	Top dec.	Bottom half	Top dec.
	(1)	(2)	(3)	(4)
Panel A				
Separation rate	0.003**	0.005***	0.000	0.009*
(standardized)	(0.001)	(0.001)	(0.004)	(0.005)
R&D activity	0.004***	0.003***	0.017***	0.017***
(standardized)	(0.001)	(0.001)	(0.003)	(0.003)
Observations	191	191	190	190
Panel B				
Hiring up	-0.005***	0.006***	0.044***	0.083***
(standardized)	(0.002)	(0.002)	(0.008)	(0.010)
R&D activity	0.000	0.008***	0.043***	0.070***
(standardized)	(0.002)	(0.002)	(0.009)	(0.009)
Mean hiring up	0.33	0.38	0.34	0.39
Observations	183	180	181	178

Notes: The table shows regression estimates of changes in productivity on worker mobility patterns and R&D activity. Regression estimates are standardized.

disconnected from prior technologies. In the Online Appendix Figures A.4 and A.6 we note that the relationships described above apply to job-to-job mobility. Similarly, in Appendix Figures A.5 and A.7, we note that the correlations are substantially weaker for mobility events with intervening unemployment.[7]

While these data patterns appear suggestive for our question of interest, we now leverage the full extent of the microdata to provide causal evidence on the suggested mechanism.

3 Empirical Motivation

Using individual-level data, we investigate the causal relationship between worker mobility and productivity. In the ideal — yet impractical and unethical — scenario, we would randomly vary the composition of workers and their knowledge within firms. To proxy for such an ideal scenario, we consider two alternative sources of quasi-experimental variation: the first focuses

[7]For separations, we include cases where the worker transitions into unemployment. For hiring, we consider transitions from one firm to another where the worker experiences a period of unemployment between the two jobs.

on new hires, while the second examines worker separations.

First, in Section 3.1, we leverage heterogeneous labor supply shocks in the local labor market, caused by negative exogenous demand shocks to local peer firms in the same industry. We exploit trade-based shift-share instruments based on firms' baseline export patterns to create these negative demand shocks (see for example Hummels et al., 2014).[8] Second, in Section 3.2, we build on a literature that exploits sudden and unexpected deaths of individuals.[9] Crucially, as described in detail in Appendix Section A.3 we only consider deaths that are unexpected, and therefore unlikely to be anticipated by firms or to be correlated with secular trends in a firm's performance. We then consider how the loss of worker-embodied knowledge reduces potential growth using product expansion data.

3.1 Local labor supply shocks

We exploit variation in the origin of newly hired workers driven by plausibly exogenous trade-based shocks. Specifically, we use trade-based shift-share instruments to generate exogenous demand shocks and examine the resulting variation in worker mobility. Leveraging firm-level export patterns from the first year of the sample, we compute firm-level demand shocks based

[8]Other studies have examined worker-associated cross-firm spillovers in different contexts. Mion and Opromolla (2014), for example, focus on whether past export experience carries over to new employers when managers move. Singh and Agrawal (2011) find that workers keep using the inventions they registered at previous employers also when they move to a new employer, and Kaiser et al. (2015) and Braunerhjelm et al. (2020) focus on patenting activity overall when knowledge workers move across firms. Meinen et al. (2022) use a control function approach to isolate the causal effect of manager mobility on internationalisation patterns of firms. Harrigan et al. (2023) find that "techies" (STEM-skill intensive workers associated with innovation) raise productivity of firms. Closest to our study, but without exploiting exogenous variations, is likely Stoyanov and Zubanov (2012) who find that the productivity gap between the new and old employer correlates with the change in productivity at a mover's new firm. Positive gaps affect the new firm, and more so if the worker is more educated or a manager. Similarly, Serafinelli (2019) analyses mobility among workers in the Italian region of Veneto, regardless of the reason of the mobility, and finds that hiring workers with experience at the most productive firms significantly increases the productivity of other firms.

[9]Becker and Hvide (2021) study the impact on young Norwegian firms when entrepreneurs die unexpectedly, while Sauvagnat and Schivardi (2023) do the same for the effect of CEO deaths on more mature firms in Italy. Jones and Olken (2005) study the impact of deaths of national leaders on the growth levels of countries, and Jaravel et al. (2018) explore the impact on inventor team members when one member of the team dies. Related, Hoey et al. (2023) study the impact of hospitalizations on the productivity of team members who continue working. Our work is most closely related to Bertheau et al. (2022) and Jäger and Heining (2019), who use large administrative datasets in Denmark and Germany, respectively, to study the impact on firms and workers when incumbent workers die. Bertheau et al. (2022) study the costs to a firm of losing a worker in terms of lost revenues, and Jäger and Heining (2019) identify which workers are complements and substitutes, respectively, to the deceased worker, by studying the effect of workers' wages when one of their colleagues passes away. Bloesch et al. (2022) use the impact of worker deaths on firm performance as a way to measure workers' holdup power. For a different outcome variable, Andersen and Nielsen (2011) study the effect of deaths that result in large windfall financial gains for close relatives of the deceased, and the subsequent investment patterns of these individuals.

on changes in global import demand for specific products in the firms' export markets. For instance, if China reduces its imports of a particular type of steel bolt, firms that exported this product to China in the baseline year would experience a larger negative shock relative to firms that either did not export these bolts or exported them to markets other than China. We then calculate the shocks to local peer firms operating in the same sector, under the assumption that negative demand shocks to a firm's local peers are inversely related to that firm's worker count.

We mimic an event study by calculating for each firm in which year its peers (i.e. firms in the same location and industry) experienced their most negative shock to world import demand for their products. We call this year the event year, which is different for each firm. We then restrict the sample to two years before and two years after that year for each firm. We only keep firms whom we observe during the entire event window in order to keep a balanced sample. We residualize each variable of relevance, i.e. firm-level trade shocks to peers, output, employment, and productivity growth, on municipality fixed effects, time-varying sector fixed effects, as well as the firm's own world import demand shock (to exploit differences in how the firm is affected by global shocks compared to how the peers are affected). We also control for the change in a firm's average level of worker fixed effects (the worker fixed effects are estimated in an AKM model, see Abowd et al., 1999, but where firm fixed effects are replaced with ten fixed effects for the size of firms and ten fixed effects for the lagged size of firms, see Card et al., 2016). The mean residuals across firms for each year relative to the event form the basis for the event.

To focus more specifically on the mechanism in our model—namely, that hired workers bring knowledge from their previous employer—we differentiate between shocks to peers with above-median labor productivity and those with below-median labor productivity. This allows us to measure whether hiring effects differ based on the productivity level of a new worker's previous employer. Moreover, since we focus on the manufacturing sector, we are not concerned that local demand effects play an important role. In contrast to for example the service sector, Swedish manufacturing firms export the vast majority of their output (Akerman et al., 2013). And of the share that is sold domestically, very little is sold to customers in the same municipality.

We report the results for the trade-shock-based events in Figures 3 and 4. First, we note that the events appear to mimic real event studies fairly well. The changes in year 0 in the residualized foreign demand levels are sharply negative. Second, in Figure 3 we note that a drop in the demand for the exports of local peers induces firms to increase the number of workers that they hire. A drop in foreign demand for a firm's peers' products by around

a third is followed by an increase in employment at the firm by around two percent. To see how workers transmit the technology of their previous employers to the new firm, we divide shocks to peers into two categories: shocks that affect above-median productivity peers and shocks that affect below-median productivity peers. Our hypothesis is that shocks to above-median peers lead to higher productivity among unaffected firms, because the workers bring knowledge about how production processes are designed in firms with high productivity. The opposite is expected to take place when workers move from less productive firms. In Figure 4 we report the impact on labor productivity. Panel a shows that when the event is based on negative shocks to highly (above median) productive firms, then labor productivity growth of the firm in question improves, likely based on the firm's ability to hire workers from more productive firms. The effect appears to be largely contemporaneous, and the increase in levels appears to remain after the event. In panel b it is clear that the effect is the opposite when the shock instead hits less productive firms, i.e. when the new hires come from less productive firms the effect on a firm's labor productivity growth is instead negative.[10] A drop in foreign demand for a firm's most productive peers' products by around 70 percent yields an increase in the productivity growth rate of around 3 percent. If a drop of the same magnitude hits the firm's less productive peers instead, there is instead a slowdown in the productivity growth rate by around 3 percent.

[10]The same figure using total factor productivity estimated using two-digit sector-specific production functions estimated according to Levinsohn and Petrin (2003) instead of labor productivity is reported in Appendix Figure A.2.

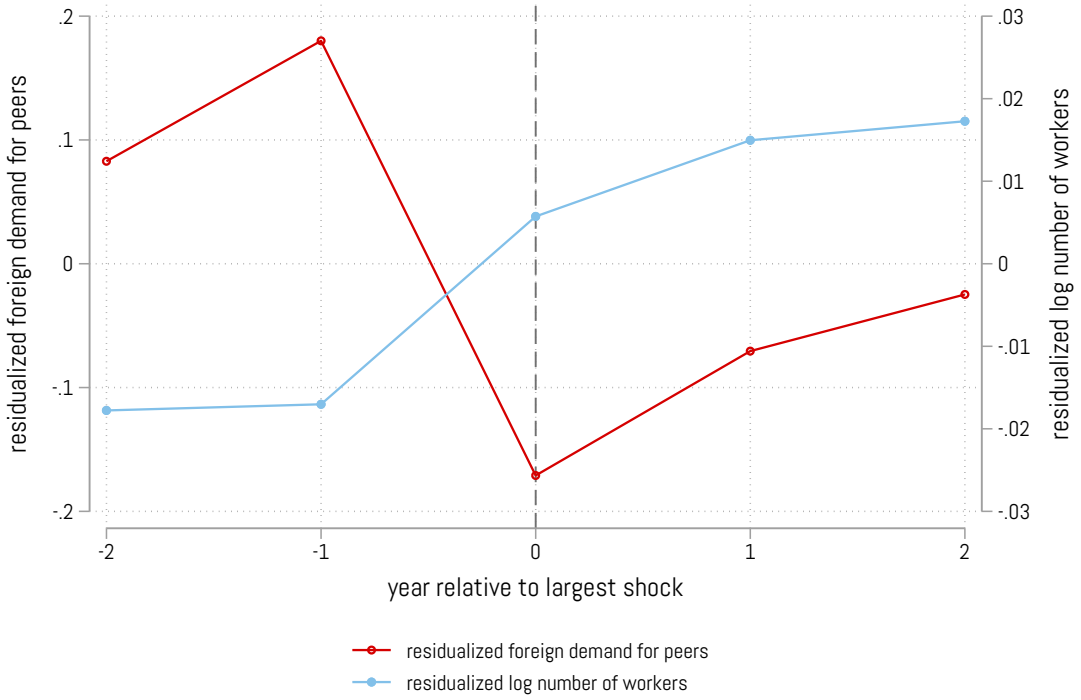
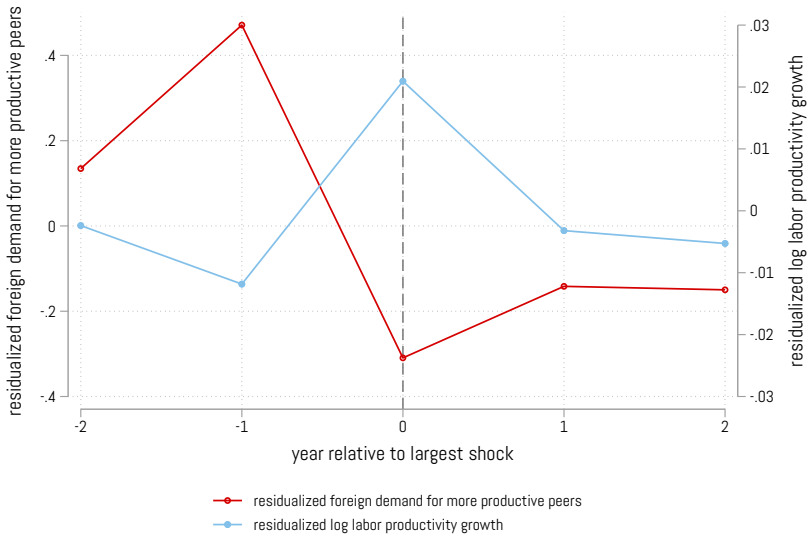
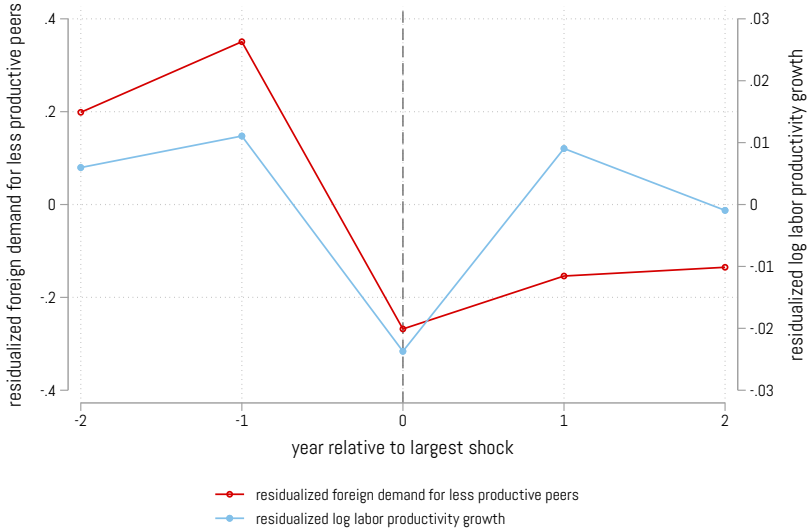


Figure 3: Effect of shocks to local peers on a firm's employment.

Notes: We mimic an event study by calculating for each firm in which year its peers (i.e. firms in the same location and industry) experienced their most negative shock to world import demand for their products. We call the year the event year, which is different for each firm. We then restrict the sample to two years before and two years after that year for each firm. We only keep firms whom we observe during the entire event window in order to keep a balanced sample. We then residualize each variable of relevance, i.e. firm-level trade shocks to peers, output, employment, and productivity growth, on municipality fixed effects, time-varying sector fixed effects, as well as the firm's own world import demand shock (to exploit differences in how the firm is affected by global shocks compared to how the peers are affected). The mean residuals across firms for each year relative to the event are plotted in the figure.



(a) Effect on productivity of shocks to peers with above-median productivity.



(b) Effect on productivity of shocks to peers with below-median productivity.

Figure 4: Causal effect of hiring on firm performance.

Notes: See Figure 3. Moreover, we separate peers into firms above and below median labor productivity. Panel a shows events based on shocks to peers with above-median labor productivity, and panel b to firms with below-median labor productivity. The same figure using total factor productivity estimated using two-digit sector-specific production functions estimated according to Levinsohn and Petrin (2003) instead of labor productivity is reported in Appendix Figure A.2.

3.2 Separations by sudden and unexpected death

A natural methodology to estimate the causal impact of an exogenous separation is to perform an event study of the effect of an exogenous death on productivity. As we are interested in potential knowledge transfers, we analyze how the likelihood of product expansion evolves during three years before and three years after a death event.[11] Specifically, we can leverage our dataset to trace the employment history of each worker, allowing us to determine their experience with each potential product line based on their past employers. For example, a worker that has been employed by a firm producing circular glass bottles of certain shape at any point in their career, is recorded as having experience in producing such glass bottles. One way to specifically test for worker effects on productivity is therefore to estimate whether losing a worker with a certain product experience negatively affects the likelihood that a firm will enter production of that specific product line.

We estimate this regression at the firm-product-year level, with the outcome variable represented by a dummy for whether a firm starts producing a certain product in a given year and the event indicator represented by events where the deceased worker had experience in producing exactly the product concerned. To account for the intensity of the treatment, we compute the number of years that a worker has experience in a specific product line, and multiply the treatment dummy with the number of years of experience. The corresponding regression specification is:

$$X_{ijt} - X_{ij,t-1} = \sum_{\tau=t-3}^{t+3} \alpha_\tau \times I_{\text{period}_\tau} \times \text{years}_{ij} + \gamma_{ij} + \eta_t + \varepsilon_{it} \tag{1}$$

where X_{ijt} takes the value 1 if firm i produces product j in year t. The variable years_{ij} indicates the number of years of experience the dying worker had of producing product j. We also control for contemporaneous firm employment.

Figure 5 reports the results from the event study on horizontal productivity. We note that the periods before the event are characterised by parallel trends. When the death occurs, there is an immediate small but statistically significant negative effect. In the first year after the death, however, the effect is much larger. In the second year there is no longer a negative effect, but since the second- and third-year changes do not revert the initial hit, the effects seem to last. A sudden and expected death lowers the likelihood of entering a new product market by almost 0.4 percent, and this corresponds to a fifth of the likelihood of entering

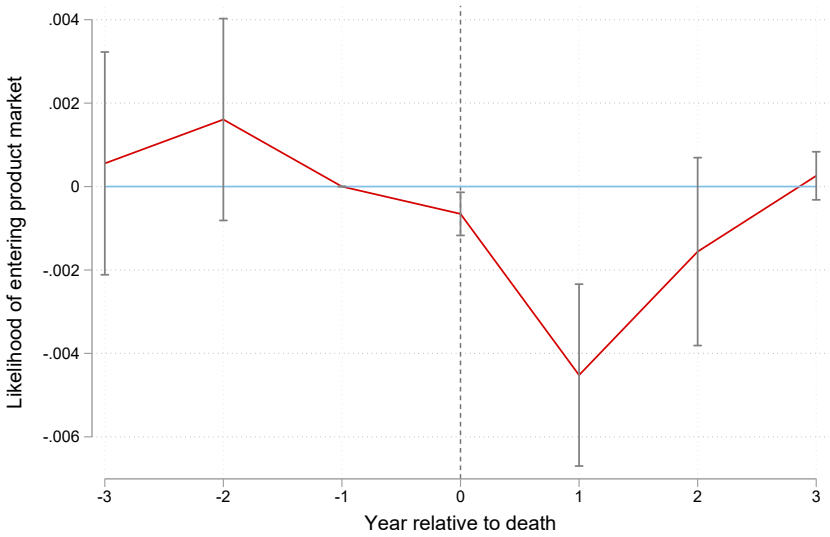
[11] Most firms experience only one death event, but in some (174) cases they experience two deaths at separate points in time. Then we use these deaths as two separate events.

a new product market by the affected firms. We conclude that an exogenous separation negatively and permanently reduces the likelihood of a firm entering production of a product in which the departing worker had specific expertise. In Appendix Figure A.3 we restrict the sample to only firms which do not replace the disappearing worker, and find that the result looks similar. We interpret these findings as capturing the value of worker-embodied knowledge that firms can potentially access when hiring a worker. While our set-up focuses on the loss of a worker rather than an addition of a worker to leverage exogeneous mobility events, our set-up focuses on potential product expansion, which we consider as a potential hire of a worker's skills in a particular product line.

To further explore whether the effects are tied to knowledge embodied in the workers that suffer an unexpected death, we explore whether the effects are different depending on the education level of the worker. In Appendix Table A.6 we regress the dummy for whether a firm starts producing a certain product on the accumulated product-specific experience of the firm's workers that die unexpectedly in the previous year. We run the regression separately for deaths of workers without and with a university degree, respectively. We find that the effects of unexpected deaths of more educated workers are substantially larger than those of less educated workers. In Appendix Table A.7 we perform the same analysis estimating instead the effect of the experience of dying workers on product-specific sales. We find that there are negative effects on product-specific experience on firm sales, and that the negative effects are, again, substantially larger for more educated workers.

We can now summarize the findings of this empirical section. We have seen that there is evidence of worker mobility patterns affecting aggregate productivity using quasi-exogenous mobility events. We found that worker mobility affects firms' potential growth, particularly so for more educated and experiences employees. These empirical findings motivate us to develop a framework to quantify the aggregate importance of worker mobility in the following sections.

Figure 5: Event study of death on product expansion.



Notes: The figure shows the impact of a worker death on whether a firm starts producing a certain product when the worker that died had experience in producing exactly that product. The corresponding regression specification is $X_{ijt} - X_{ij,t-1} = \sum_{\tau=t-3}^{t+3} \alpha_\tau \times I_{\text{period}_\tau} \times \text{years}_{ij} + \gamma_{ij} + \eta_t + \varepsilon_{it}$ where X_{ijt} takes the value 1 if firm i produces product j in year t and years_{ij} indicates the number of years of experience the dying worker had of producing product j. We also control for contemporaneous firm sales.

4 Theory

In the following, we describe a framework used to estimate the effect of worker disappearances on a balanced growth path. The theory describes a multi-worker-firm as a learning and innovation environment where productivity change and knowledge diffusion originates. In this economy, firm output per worker changes due to worker mobility, but also in the absence of worker mobility due to in-house innovation.

In the following, we first lay out the details of the economy (cf. Section 4.1) and describe the value functions (cf. Section 4.2). In this section, we will show that the worker-firm surplus admits an affine representation, which allows us to understand the interplay of firm productivity, size and time. We then derive the laws of motion for the productivity distributions (cf. Section 4.3) and the balanced growth path of the economy (cf. Section 4.4), using the previous insights and auxiliary assumptions. We first outline a model without on-the-job search in order to facilitate exposition. In Section 4.5, we relax this assumption and show how the main model equations change with on-the-job search. All derivations are relegated to Appendix Section A.1.

4.1 Environment

Physical Environment The economy is set in continous time and there is no aggregate uncertainty. The labor market consists of a measure of workers $i \in 1, ..., N_t^I$ and a measure of firms $j \in 1, ..., N_t^J$. Workers are endowed with one unit of time each period, that they supply inelastically to the labor market. Both firms and workers are risk neutral, infinitely lived, and discount the future at the risk free rate r. They have heterogeneous and time-varying productivity, denoted p_{it} for workers and P_{jt} for firms. Firm productivity follows an endogeneous distribution function, denoted as $G(P, t)$. Firms produce a single homogeneous good with output Y according to the constant returns to scale technology $Y(P, N, t) = P_t N_t$.[12]

Workers can be employed or unemployed. There is a share u_t of unemployed workers, whose productivity follows the endogeneous productivity distribution $F(p, t)$. When employed, workers can be exogeneously displaced. If unemployed, they receive unemployment benefit $b(t)$, and have a chance to meet a new firm every period. We assume that firms and workers meet each other in a frictional labor market governed by random search. There is no on-the-job search (as in Bertheau et al., 2022).

Each period, through the entry of new labor market participants, the work force grows by a factor μ_I. Skills of the new labor market entrants are drawn from the productivity distribution $w(p, t)$. Thereafter, worker skills evolve with learning on the job and job mobility. Finally, each period new firms enter the market, with initial size 0, at rate μ_J. New firms imitate existing technology such that they draw a productivity from the endogeneous incumbent firm productivity distribution $G(P, t)$.

Firm and worker productivity evolution An individual firm's productivity varies over time through firm innovation and worker mobility. In both cases, when firms meet a new worker or encounter a new technology with productivity ρ, they adopt the new technology whenever it exceeds the current state of the art at the firm, hence the firm updates its productivity to $\max\{\rho_{it}, P_{jt}\}$. Similarly, workers with productivity p_{it} adopt the current technology of the firm to $\max\{p_{it}, P_{jt}\}$.[13] While our model focuses on transferable productivity, the literature has attributed a non-negligible role to non-transferable productivity components, notably

[12] Constant returns are a crucial assumption that allows us to obtain a balanced growth path in this economy. Note that in Bilal et al. (2022) individual firm technology is also constant returns to scale, but at the aggregate level, decreasing returns result from consumer demand with constant elasticity of substitution across goods.

[13] The notion that firm technology and worker skills become more similar over time has been used previously for instance in Lise and Postel-Vinay (2020) or Bárány and Holzheu (2024). Here we assume an instantaneous adaptation of technologies.

when discussing the effects of mass-layoffs.[14] To allow our model to capture productivity losses due to such productivity components, we allow worker displacements to disrupt firm productivity. Without modelling these alternations in detail, we consider them reflective of organizational disruptions, adaptation difficulties or loss in non-transferable knowledge after a previous worker configuration changes.

Specifically, firms search for workers, and meet a new worker ι at rate λ each period. The productivity of the encountered worker, $p_{\iota t}$, is drawn from the endogeneous skill distribution of unemployed workers $F(p,t)$. When a worker with productivity $p_{\iota t}$ joins the firm, firm productivity increases if $p_{\iota t} > P_{jt}$. Hence, a firm of productivity P meets a more knowledgeable worker at rate $\bar{F}(P,t)$. Otherwise, the hired worker's productivity is updated to the firm's current productivity level, no change of firm level productivity occurs, and the firm gains a new worker. As a result, a firm increases its productivity through worker arrival with probability $\lambda\bar{F}(P,t)$. When a worker leaves the firm, we assume that the firm experiences a productivity adjustment to αP with $0 < \alpha < 1$. At the same time, we assume that the worker carries with himself his initial level of productivity, P. These assumptions reflect the idea that a worker's disappearance can create disruptions at the firm, while the re-entry of a worker with the previous level of productivity resolves the initial disruption.

The productivity of the firm also evolves through firm-level innovation by drawing from the exogenous idea distribution $V(P,t)$. We denote this idea generation as within firm innovation. At rate β, the firm draws from the idea distribution $V(P,t)$, and adjusts its productivity whenever it is worthwhile doing so. This occurs at rate $\bar{V}(P,t)$. Figure 6 schematically represents these adaptation processes, using a discrete time scale for illustration purposes.

The search and separation process changes the size of the firm over time. We denote the total number of workers at the firm with N_t. Note that innovation and worker hiring can only increase productivity or leave it unchanged, whereas worker departures can decrease productivity.

Contracts and Negotiations We follow Bilal et al. (2022) and Bilal et al. (2021) regarding the negotiation protocol within the firm. In our baseline set-up without on-the-job search, we make a single assumption on contracting, that is that negotiations involve take-it-or-leave-it offers. Notably, this implies that workers receive their unemployment value when being hired from unemployment, and that therefore all workers accept to work for all firms. We describe changes to this contracting framework in Section 4.5.

[14] See for instance Neal (1995), Parent (2000), Carrington and Fallick (2017), Kletzer (1996), Kambourov and Manovskii (2009), Milgrom (2023).

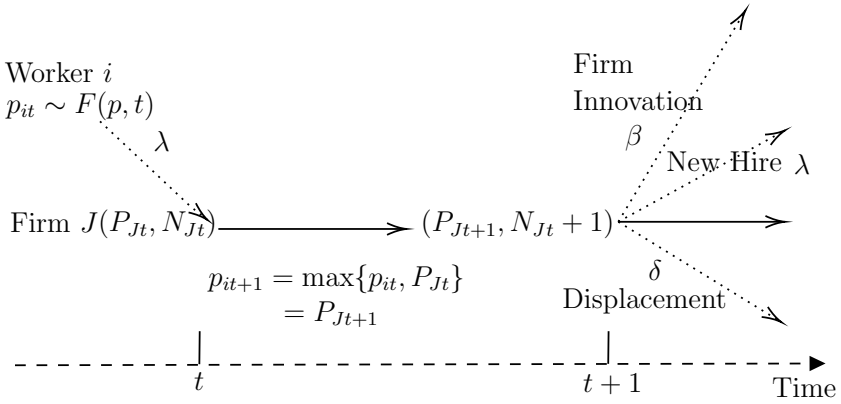


Figure 6: Mobility and Adaptation

Notes: The figure shows the evolution of productivity within the firm together with the events possibly affecting the firm on a time-line.

4.2 Value function and productivity distributions

Value Functions We can now write the value of the firm and of unemployed workers. First consider the value of unemployment $U(t)$. It is composed of the flow value of receiving unemployment benefits $b(t)$ and the option value of matching with a firm. Given the negotiation protocol with take-it-or-leave-it offers, the worker is offered his second best outcome when hired from unemployment, leaving his value before and after job finding unchanged. Hence the value of unemployment is simply

$$rU(t) = b(t) + U_t$$

where $U_t := \lim_{\Delta \to 0} \frac{U(t+\Delta)-U(t)}{\Delta}$. Denote with $\Omega(P, N, t)$ the joint value of the firm and its firm-associated workers. With some abuse of notation, we will denote the marginal values of a change in firm size, Ω_N, with $\Omega_N := \Omega(P, N, t) - \Omega(P, N-1, t)$, and the marginal value of a change in productivity to value P' as $\Omega_{P',P} := \Omega(P', N, t) - \Omega(P, N, t)$.

The joint value $\Omega(P, N, t)$ is composed of the flow output $Y(P, N, t)$ and the option value of the firm's team. The option value is composed of three terms:

- EU mobility: the change in the value due to an exogenous separation or a labor market exit of one firm-associated worker, occurring with probability δ,
- UE mobility: the increase in the value due to the matching with an unemployed worker at rate λ
- Innovation: the increase in the value due to innovation within the firm at rate β

We will explain and evaluate these terms in turn. In case of an EU mobility event, the firm looses a worker such that the firm's team experiences a change in value due to a) the new unemployment status of the displaced worker, b) the change in the team size and c) the change in firm productivity due to productivity disruption, leading to change of productivity to $\tilde{P} = \alpha P$. These three changes total the value of

$$\left(U(t) - \Omega_N - \Omega_{\tilde{P},P}\right)$$

In the case of a UE hiring event, the firm expands its workforce and updates its productivity if the new worker has a productivity exceeding the current firm productivity P. This involves a change in the firm's team value resulting from a) the increase in the value due to the expansion of the team, b) the loss of the unemployment value of the new hire, and c) the increase in the value due to a potential productivity upgrading. These three forces total a change in value of

$$\left(\Omega_N - U(t) + \int_P^\infty \Omega_{P',P} dF(P',t)\right)$$

Finally, innovation at rate β leads to an increase in the team's value due to innovation of $\int_P^\infty \Omega_{P',P} dV(P',t)$. We bring together these different forces and write the value of the firm coalition as

$$\begin{aligned} r\Omega(P,N,t) &= Y(P,N,t) + \Omega_t \\ \text{(EU Mobility)} &+ \delta\left(U(t) - \Omega_N - \Omega_{\tilde{P},P}\right) \\ \text{(UE Mobility)} &+ \lambda\left(\Omega_N - U(t) + \int_P^\infty \Omega_{P'P} dF(P',t)\right) \\ \text{(Innovation)} &+ \beta\left(\int_P^\infty \Omega_{P',P} dV(P',t)\right) \end{aligned}$$

The incentive compatibility constraints ensure that the firm makes non-negative profits and that the workers' value in employment, denoted $W(P,t)$, is not smaller than the unemployment value, such that i) $\Omega(P,N,t) \geq NU(t)$ and ii) $W(P,t) \geq U(t)$ hold at all points in time. The definition of the lowest support of productivity P ensures that these two criteria are satisfied on all points of the productivity distribution. We derive the continuous time Bellman equation from the discrete time analogue in Appendix Section A.1.

Surplus Representation It is useful to represent the value function in form of the worker-firm surplus $S(P,N,t)$ such that $\Omega(P,N,t) = S(P,N,t) + NU(t)$. We can write the surplus

value equation as

$$rS(P,N,t) = (P - b(t))N + S_t + (\lambda - \delta)\, S_N + \omega(P,N,t) \tag{2}$$

where the last term denotes productivity changes due to mobility and innovation, $\omega(P,N,t)$

$$\omega(P,N,t) = \left(\lambda \int_P^\infty S_{P',P} dF(P',t) + \beta \int_P^\infty S_{P',P} dV(P',t) - \delta S_{\tilde{P},P}\right)$$

Using this equation, we show that the surplus equation satisfies an affine representation such that $S(P,N,t) = N\hat{S}(P,t) + S^0(P,t)$. Firm size affects the worker-firm surplus hence only linearly in the slope of the worker-firm surplus while leaving the intercept independent of firm size (cf. Appendix Section A.1 for the derivation).

Result 1 (Affine Surplus Representation) *The surplus equation is affine in firm size* $S(P,N,t) = N\hat{S}(P,t) + S^0(P,t)$

This finding allows us to define a balanced growth path in Section 4.4.

4.3 Productivity Distributions

We can now derive the law of motion of the endogenous distributions of firm productivity $g(P,t)$ and of unemployed workers $f(P,t)$, by combining the in-flows and out-flows of workers and tracing instances of innovation activity. We first turn to the distribution of firm productivity. Inflows into the firm productivity distribution $g(P,t)$ derive from four different sources. First, a measure $G(P,t)$ of firms finds a P-skilled unemployed worker at rate $\lambda f(P,t)$. Second, a measure $G(P,t)$ of firms finds productivity P through innovation at rate $\beta v(P,t)$. Third, a measure δ of firms experiences a disappearance and sees their productivity adjust to $\tilde{P} = \alpha P$. The inflow of new firms with productivity P' is hence $g(\tilde{P}/\alpha, t)\delta$. Finally, there is new entry of firms at rate $\mu_f g(P,t)$. The outflow is composed of the flip side of these events. First, a measure $g(P,t)$ of firms finds a higher-skilled worker at rate $\lambda \bar{F}(P,t)$. Second, a measure $g(P,t)$ of firms finds a higher-skilled worker at rate $\lambda \bar{F}(P,t)$, and finally, a measure $g(P,t)$ experiences adaptation and productivity change at likelihood $g(P,t)\delta$. Hence, we can write

the law of motions as

$$\frac{\partial g(P,t)}{\partial t} = \underbrace{\underbrace{f(P,t)G(P,t)\lambda}_{\text{Mobility Upgrade}} + \underbrace{\beta v(P,t)G(P,t)}_{\text{Innovation}} + \underbrace{\delta g\left(P/\alpha,t\right)}_{\text{Displacement}} + \underbrace{\mu g(P,t)}_{\text{New Firms}}}_{\text{Inflow}} \\ \underbrace{- \underbrace{\lambda g(P,t)\bar{F}(P,t)}_{\text{Mobility Upgrade}} - \underbrace{\beta g(P,t)\bar{V}(P,t)}_{\text{Innovation}} - \underbrace{g(P,t)\delta}_{\text{Displacement}}}_{\text{Outflow}} \tag{3}$$

We also keep track of the productivity distribution of unemployed workers $f(P,t)$. To do this, we consider the change in the share of unemployed workers with skill level P due to inflows and outflows from the pool of the unemployed. On the one hand, a measure $\lambda f(P,t)\frac{N_t^J}{u_t N_t^I}$ finds a new job. On the other hand, the inflow into unemployment derives from a measure $g(P,t)\delta\frac{N_t^J}{u_t N_t^I}$ who enter unemployment after displacement from firms with productivity P and a measure $\mu_w w(P,t)\frac{N_t^I}{u_t N_t^I}$ who newly enter the job market. By bringing these effects together, we obtain

$$\frac{\partial f(P,t)}{\partial t} = \underbrace{\underbrace{\delta g(P,t)\frac{N_t^J}{u_t N_t^I}}_{\text{Displacement}} + \underbrace{\mu w(P,t)\frac{N_t^I}{u_t N_t^I}}_{\text{New Entrants}}}_{\text{Inflow}} - \underbrace{\lambda f(P,t)\frac{N_t^J}{u_t N_t^I}}_{\text{Outflow: New Hires}} \tag{4}$$

4.4 Balanced growth path of the economy

We can now define an equilibrium and a balanced growth path in this economy.

Definition 1 (Equilibrium) *Given the initial productivity distributions $f(z,0)$ and $g(z,0)$ and the exogeneous idea distributions $v(z,0)$ and $w(z,0)$ as well as initial worker and firm sizes N_0^J, N_0^I, an equilibrium is a set of three functions (f,g,S) such that i) given (f,v), S satisfies the surplus equation for all (z,N,t) as in equation 2, iii) (f,g) satisfy the laws of motion in equations 4 and 3.*

Our interest in a study of the growth rate of the economy motivates the following definition of the balanced growth path of this economy.

Definition 2 (Balanced Growth Path) *A balanced growth path is a number γ such that*

$$\begin{aligned} F(P,t) &= \Phi(Pe^{-\gamma t}) \\ G(P,t) &= \Theta(Pe^{-\gamma t}) \\ S(P,N,t) &= e^{\gamma t}\sigma(Pe^{-\gamma t},N) \\ W(P,t) &= \Pi(Pe^{-\gamma t}) \\ V(P,t) &= \Upsilon(Pe^{-\gamma t}) \end{aligned}$$

for all (P,N,t) with the initial conditions $\Phi(P),\Theta(P),\Pi(P),\Upsilon(P)$ and (Φ,Θ,σ) are an equilibrium.

It is immediate that we can find a balanced growth representation of the surplus function given its affine representation such that $S(P,N,t) = N\hat{S}(P,t)+S^0(P,t) = \hat{\sigma}(Pe^{-\gamma t})N+\sigma_0(Pe^{-\gamma t}) = \sigma(Pe^{-\gamma t},N)$, cf. Appendix Section A.1.4. We study the balanced growth path of the productivity distributions next. Following the definition of the balanced growth path, we can define the densities of the productivity distributions.[15] To proceed, we will make the following two assumptions.

Assumption 1 *All initial distributions $D \in \{\Phi,\Theta,\Pi,\Upsilon\}$ have a Pareto tail with parameters θ and k_D, such that*

$$\lim_{x\to\infty} \frac{1-D(x,0)}{x^{-1/\theta}} = k_D$$

Assumption 2 *The two distributions $D \in \{\Pi,\Upsilon\}$ of new ideas through innovation (Υ) and the distribution of new workers (Π) evolve with the distribution of worker productivity Φ such that*

$$1-D(x,t) = \alpha_D k_\Phi x_t^{-1/\theta}$$

While the first assumption expresses that the stock of ideas is inexhaustible (and follows Lucas and Moll, 2014), the second assumption flexibly links the current distribution of innovation and worker ability to the distribution of worker productivity. We believe that such a relationship makes intuitive sense: in the long run, the education of labor market entrants evolves with the current state of knowledge in the economy and so does the stock of innovative ideas.

[15] Notably, these are $f(P,t) = e^{-\gamma t}\Phi'(Pe^{-\gamma t})$, $g(P,t) = e^{-\gamma t}\Theta'(Pe^{-\gamma t})$. As a result, $\frac{\partial f(P,t)}{\partial t} = -\gamma e^{-\gamma t}\Phi'(Pe^{-\gamma t}) - P\gamma(e^{-\gamma t})^2\Phi''(Pe^{-\gamma t})$, and $\frac{\partial g(P,t)}{\partial t} = -\gamma e^{-\gamma t}\Theta'(Pe^{-\gamma t}) - P\gamma(e^{-\gamma t})^2\Theta''(Pe^{-\gamma t})$

Using equations 3 and 4, together with assumptions 1 and 2, we obtain two equations that characterize the limiting equilibrium in the economy

$$\delta \frac{k_\Theta}{k_\Phi} = \lambda + \frac{\gamma}{\eta_p \theta} + \frac{\mu_w N^I}{N^J} \alpha_\Pi \tag{5}$$

$$\gamma = \theta \left(\lambda \frac{k_\Phi}{k_\Theta} + \beta \alpha_\Upsilon \frac{k_\Phi}{k_\Theta} + \mu_f + \delta \left(\alpha^{\frac{1-\theta}{\theta}} - 1 \right) \right) \tag{6}$$

where $\frac{N_t^J}{u_t N_t^I} = \eta_p$ (cf. Appendix Section A.1.5). Equation 6 mirrors an intuitive accounting relationship between the growth rate in the economy, γ and the idea flows in it, emanating from worker mobility at rate λ, innovation at rate β, new firm arrival at rate μ_f or worker disappearance at rate δ. These different flows affect growth differently depending on the idea source and the location parameters characterizing the idea source (represented by the scaler α_Υ and the relative weights $\frac{k_\Phi}{k_\Theta}$). Equation 5 equates the long-run in and outflows of workers into the pool of the unemployed, weighted by the location parameters of their respective origin idea distribution. Intuitively, as some idea sources are better than others, the long-run distribution of ideas is affected differently, for example, by new entrants (with location parameter α_Π) than by new job entrants.

4.5 Extension with on-the-job search

So far, we have entertained the assumption that workers cannot search on the job. In the following, we relax this assumption by allowing workers to move across jobs without intervening unemployment spells. Given our set-up, we will show that we can characterize mobility decisions of workers and that the previous insights pertain with only minor modifications. We will then show that the equilibrium equations on the balanced growth path feature an additional margin due to job mobility. In the following, we will first describe additional assumptions necessary for the case of job-to-job mobility before extending the model equations.

Additional Assumptions We assume that with chance $s\lambda(1-u_t)$, a firm receives a job offer from an employed worker and with chance λu_t from an unemployed worker. Similarly, a firm looses a worker to another firm at rate $\tilde{\lambda} s(1-u_t)$. We assume that job-to-job mobility is a less disruptive process than displacement such that no productivity disturbance occurs at the firm due to job-to-job mobility.[16]

[16]This is a necessary assumption to preserve tractability. Under this assumption, mobility leaves the joint surplus of the worker firm coalition unchanged (as in Postel-Vinay and Robin, 2002), which facilitates the analysis considerably. In practice, job dissolutions due to layoffs are arguably less amicable than quits, which

Contracting and Mobility Contracts follow the sequential auction framework in Bilal et al. (2021) that is i) firms can vary contract offers according to characteristics of workers, ii) firms can counter offers received by employees, and iii) contracts are only renegotiated with mutual consent after a credible threat. These assumptions clarify that a worker in negotiations between two firms will always receive the second best offer. Moreover, the worker will move to the firm with the highest marginal value. As an incumbent worker only contributes to the employer-worker-firm coalition through production, but potentially contributes to learning at a receiving firm, we can analyze the mobility decisions of the worker. Specifically, the marginal value at an incumbent firm is

$$\Omega(P, N, t) - \Omega(P, N-1, t) := \Omega_N(P, N, t),$$

and at the outside firm

$$\begin{aligned}&\Omega(\max\{P', P\}, N'+1, t) - \Omega(P', N', t)\\ &= \Omega_N(P', N'+1, t) + (\Omega(P, N'+1, t) - \Omega(P', N'+1, t))\, I_{P-P'\geq 0}.\end{aligned}$$

We hence know that the contract C is such that

$$C = \min\left\{\Omega_N(P, N, t), \Omega_N(P', N'+1, t) + (\Omega(P, N'+1, t) - \Omega(P', N'+1, t))\, I_{P-P'\geq 0}\right\}.$$

We know that the worker $p_{it} = P$ meeting a firm $P_{jt} = P'$ is moving to the outsider firm if

$$\Omega_N(P, N, t) \leq \Omega_N(P', N'+1, t) + (\Omega(P, N'+1, t) - \Omega(P', N'+1, t))\, I_{P-P'\geq 0}.$$

To further study the direction of worker mobility, we follow a guess-and-verify approach. Specifically, we guess that surplus continues to take the form of an affine representation in firm size even with on-the-job search. We will verify this assumption later on.

Assumption 3 (Affine Representation) *The surplus equation satisfies*

1. *Surplus is affine in firm size N: $S(P, N, t) = \hat{S}(P, t)N + S^0(P, t)$.*
2. *$\hat{S}(P, t), S^0(P, t)$ are weakly increasing in P.*

Given this guess, the mobility equation hence simplifies to

$$\begin{aligned}\Omega_N(P, N, t) &\leq \Omega_N(P', N'+1, t) + (\Omega(P, N'+1, t) - \Omega(P', N'+1, t))\, I_{P-P'\geq 0}\\ \hat{S}(P, t) &\leq \hat{S}(P', t) + \left(\left(\hat{S}(P, t) - \hat{S}(P', t)\right)(N'+1) + \left(S^0(P) - S^0(P')\right)\right) I_{P-P'\geq 0}\end{aligned}$$

could rationalize such a distinction.

Using our assumptions, we know that this always holds true, irrespective of whether the worker meets a more or less productive firm. Concretely, if the outside firm is more productive than the incumbent, no learning takes place but the marginal return is higher at the outside firm. If the outside firm is less productive than the current firm, then the difference in marginal value is at least as high as the benefit from learning, such that the worker moves as well. Note that this setting is different from the standard mobility choices in Postel-Vinay and Robin (2002) where workers move to an outside firm only if its productivity exceeds the productivity of the incumbent firm.[17]

Value Functions and Distribution Functions Using these insights, we can write the surplus equation as

$$\begin{aligned} rS(P,N,t) &= N\left(P-b(t)\right)+S_t \\ \text{(EU Mobility)} &+ \delta\left(-S_N+S_{\tilde{P},P}\right) \\ \text{(Mobility)} &+ \lambda\left(u_t\int_P^\infty S_{P',P}dF(P',t)+s(1-u_t)\int_P^\infty S_{P',P}dG(P',t)\right) \\ &+ \lambda\left(S_N-s(1-u_t)\int_{\underline{P}}^\infty S_{N'}(P',t)dF(P',t)\right) \\ \text{(Innovation)} &+ \beta\int_P^\infty S_{P',P}dV(P',t) \end{aligned}$$

Compared to the setting without on-the-job search, we find that the option value features two additional terms. The first term is the expected gain due to learning from workers hired from other firms and the second term is the loss in value at the origin firm associated with a job-to-job mobility.[18] We verify that this surplus equation permits an affine representation (cf. Appendix Section A.1.7).

[17] As a result, in this model, there is no surplus renegotiation at the job through job search - while there is a potential renegotiation due to the incentive compatibility constraints.

[18] Note that due to the affine representation, $S_{N'}(P',t)$ is independent of firm size at the origin firm N'.

The productivity distribution of firms similarly changes to

$$\frac{\partial g(P,t)}{\partial t} =$$
$$\underbrace{\underbrace{\beta v(P,t)G(P,t)}_{\text{Innovation}} + \underbrace{\mu_f g(P,t)}_{\text{New Firms}} + \underbrace{g(P,t)G(P,t)\lambda s(1-u)}_{\text{Mobility Upgrade EE}} + \underbrace{f(P,t)G(P,t)\lambda u}_{\text{Mobility Upgrade UE}}}_{\text{Inflow 1}}$$
$$+ \quad \underbrace{\delta g\left(P/\alpha, t\right)}_{\text{Inflow 2: Displacement}}$$
$$- \underbrace{\underbrace{\lambda u g(P,t)\bar{F}(P,t)}_{\text{Mobility Upgrade UE}} + \underbrace{\lambda s(1-u)g(P,t)\bar{G}(P,t)}_{\text{Mobility Upgrade EE}} + \underbrace{\beta g(P,t)\bar{V}(P,t)}_{\text{Innovation}} + \underbrace{g(P,t)\delta}_{\text{Displacement}}}_{\text{Outflow}}$$

Compared to the flow equation without job-to-job mobility, we find two new terms that are associated, respectively, with workers' job-to-job mobility. Note that the distribution function for unemployed worker productivity remains unaffected. Taking these insights together, we find that the limiting equation on the balanced growth path is therefore altered to

$$\gamma = \theta \left(\lambda \left(\frac{k_\Phi}{k_\Theta} u + s(1-u) \right) + \beta \alpha_\Upsilon \frac{k_\Phi}{k_\Theta} + \mu_f + \delta \left(\alpha^{\frac{1-\theta}{\theta}} - 1 \right) \right)$$

In the following section, we will demonstrate how we can apply the equilibrium equations to the data. We will then empirically illustrate its implications for quantifying the importance of worker mobility for aggregate growth.

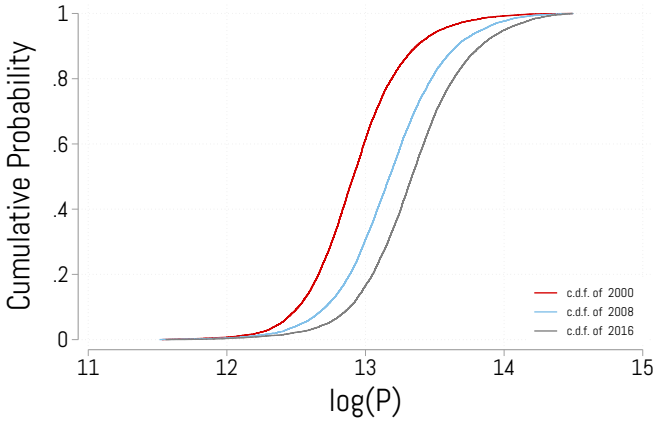
5 Results

In the following, we show quantitative results from the model using micro-economic firm data on output and worker mobility events. We first present the calibration argument in section 5.1, before proceeding to show the empirical results in section 5.2. After presenting parameter estimates and the growth decomposition into parts deriving from mobility and innovation, we present an application in section 5.3. Through a sub-sample analysis, we demonstrate the change in the growth decomposition due to a recent decline in labor mobility.

5.1 Calibration argument

The productivity distribution for Swedish firms, as shown in Figure 7, indicates a noticeable rightward shift over time. In this section, we leverage the model equations to quantify the importance of labor mobility for this shift in the productivity distribution. To do so, we

Figure 7: Shifting Productivity distribution



Notes: The figure shows the empirical density of firm productivity for three years, focusing on the core of the productivity distribution.

leverage the two equilibrium equations, here recast as equations 7 and 8, which describe the equilibrium unemployment u and economic growth γ given labor market and idea distribution parameters

$$\delta \frac{k_\Theta}{k_\Phi} = \lambda + \frac{\gamma}{\eta_p \theta} + \frac{\mu_w N^I}{N^J} \alpha_\Pi \tag{7}$$

$$\gamma = \theta \left(\lambda \left(\frac{k_\Phi}{k_\Theta} u + s(1-u) \right) + \beta \alpha_\Upsilon \frac{k_\Phi}{k_\Theta} + \mu_f + \delta \left(\alpha^{\frac{1-\theta}{\theta}} - 1 \right) \right) \tag{8}$$

To bring these equations to the data, we specialize the productivity distributions as Pareto distributions with countercumulative distribution function $\text{Prob}(X > x) = \kappa^{1/\theta} x^{-1/\theta}$. We would now like to pin down the labor market parameters and (long-run) idea distribution parameters of the model by leveraging firm productivity and worker mobility data. Specifically, we use firm-level data on a) average worker productivity $P = Y/N$, obtained as (revenue-based) value-added per worker, b) mobility events, obtained as indicators whether firms experience a new arrival of a worker - including whether the new hire is a labor market entrant, moves from unemployment or has previously worked at other firms - or a worker departure - including whether the departure was exogenous or not - , c) expenditure data on R&D as well as d) demand shocks as obtained through shift-share instruments, building on Hummels et al. (2014). We leverage shift-share instruments to control for revenue-based changes in value added per worker due to demand shocks, which we consider outside the focus of our model on the long-run balanced growth path. We will show in the following how

we use this data for recovering the parameters of the model.[19] Our goal is to pin down the parameters such that they are consistent with a long-run balanced growth path of which we observe the characteristic growth rate and unemployment rate.

First, the calibration of labor market parameters mostly follows standard practices and leverages worker mobility data. In the data, we can estimate the likelihood of firms to hire a worker from unemployment, $UE = u\lambda$, and the likelihood of firms to hire a worker from employment, $EE = \lambda(1-u)s$, as well as the average firm size $f = \frac{(1-u)N^I}{N^J}$ and firms' likelihood of loosing a worker to unemployment, δ. We obtain estimates of these rates with simple sample averages over the firm distribution. Specifically, we estimate δ from EU mobility events as the likelihood of firms to experience a worker exit.

$$\text{Prob}\{\text{EU}\} = \delta$$

such that $E_\Theta[EU] = \hat{\delta}$, where the subscript Θ denotes averages over the firm distribution. Similarly, we estimate $\hat{f} = E_\Theta\left[\frac{N^I(1-u)}{N^J}\right]$, and we estimate UE and EE from UE and EE mobility events as firms' likelihood of experiencing such a worker entry

$$\text{Prob}\{\text{Hire—UE Transition}\} = UE$$
$$\text{Prob}\{\text{Hire—EE Transition}\} = EE$$

such that $E_\Theta[Hire|\text{UE Transition}] = \hat{UE}$ and $E_\Theta[Hire|\text{EE Transition}] = \hat{EE}$. From these estimates, the model predicts a mapping to pin down μ_w and μ_f.[20]

To pin down the remaining idea distribution parameters, we use microeconomic data on worker mobility events and firm productivity trajectories. First, we can pin down productivity losses due to worker mobility, α, using firms' mobility events such that in the event of an exit of a worker to unemployment, productivity changes to αP. Specifically, to estimate the skill depreciation parameter, α, we perform a regression of current productivity levels on lagged productivity levels, allowing for a difference in slope at those firms with an exogenous

[19] In a computerized simulation exercise, we have shown success of this identification and estimation scheme in line with the model.

[20] The equilibrium relationship for the pool of unemployed, requiring inflows into unemployment to balance outflows from unemployment, yields

$$\mu_I = (\lambda u - \delta)\frac{N^J}{N^I} = \frac{(UE - \delta)(1-u)}{f}.$$

Constancy of the average firm size f implies $\mu_I = \mu_f$. Finally, the fact that new workers always enter the economy through unemployment implies $\mu_I = \mu_w u$. More details can be found in Appendix section A.1.8.

displacement event. By controlling for relevant covariates, the coefficient on the interaction term captures the negative impact of unexpected deaths on productivity. Hence, on the sample of firms, indexed with letter j, we estimate ξ_1 using the regression specification

$$P_{j,t+1} = \xi_0 P_{j,t} + \xi_1 P_{j,t} \times I_{EU} + x_{j,t} b + \varepsilon_{j,t+1}$$

where ε denotes simple measurement error and x denotes a set of covariates. While the theoretical model specifies the disturbance (cast in discrete time formulation) $P_{j,t+1} = \alpha P_{j,t}$, we choose a more flexible specification empirically where we interpret the theoretical disturbance $1 - \alpha$ as the change in autocorrelation due to an exogenous displacement event, ξ_1, while allowing for empirical covariates that are outside of the theoretical model.[21] Second, we can calibrate the likelihood of innovation, β, using R&D data. To do this, we factor the likelihood of productivity increases in the absence of mobility into two terms: a) the likelihood of innovation and b) the likelihood of productivity increases given innovation

$$\text{Prob}\{\Delta P > 0 | \text{No Mobility}\} = \text{Prob}\{\text{Innov.}\}\text{Prob}\{\Delta P > 0 | \text{Innov.\&No Mob}\}.$$

For the estimation of the first part, we transform the observed expenditure data on R&D into firm-level identifiers of innovative activity taking into account that the level of innovation might depend on observable characteristics. We hence estimate $\text{Prob}\{\text{Innov}\} = G(z_{j,t}\beta)$ using a logit regression based on R&D expenditures and a vector of predictive variables z, including labor productivity, firm size, sector and year effects as well as shift-share demand shocks. Using the predictive value $\hat{\text{Innov}}$, we can obtain an estimate of β

$$\text{Prob}\{\hat{\text{Innov}}\} = \beta$$

such that $E_\Theta[\hat{\text{Innov}}] = \hat{\beta}$.

Third, we can use the model's predictions on the likelihood of productivity increases in specific cases to calibrate the tail parameter of ideas, θ. In the absence of worker mobility, the model predicts productivity increases through innovation at rate $\bar{\Upsilon}(P,t)$, such that

$$\text{Prob}\{\Delta P > 0 | \text{Innov.\&No Mob}\} = (\alpha_\Upsilon \kappa_\Phi)^{1/\theta} (P e^{-\gamma t})^{-1/\theta}$$

In the case of mobility from labor market entrants, the likelihood of productivity increases is $\bar{\Pi}(P,t)$, such that

$$\text{Prob}\{\Delta P > 0 | \text{Enter}\} = (\alpha_\Pi \kappa_\Phi)^{1/\theta} (P e^{-\gamma t})^{-1/\theta}$$

[21] In the computerized model simulation and estimation, we therefore do not include covariates.

In the event of UE or EE mobility, the likelihood is

$$\text{Prob}\{\Delta P > 0|\text{UE}\} = k_{\Phi}^{1/\theta}(Pe^{-\gamma t})^{-1/\theta} \text{ and } \text{Prob}\{\Delta P > 0|\text{EE}\} = k_{\Theta}^{1/\theta}(Pe^{-\gamma t})^{-1/\theta}$$

respectively. These three equations jointly suggest a regression specification to estimate θ using the likelihood of productivity changes, averaged over productivity levels P and time t, forming $n = 1, ...N$ observations, such that

$$\begin{aligned}\log E\left[\text{Prob}\{\Delta P > 0|\text{No EU Mob.}\}\right]_{n,t} &= c_{\text{Innov}} + c_{\text{Enter}} + c_{\text{UE}} + c_{\text{EE}} - 1/\theta \log P_{n,t} + \gamma/\theta t + u_{n,t} \\ &= c_0 - 1/\theta\left(\log P_{n,t} - \gamma t\right) + u_{n,t}\end{aligned}$$

where $u_{n,t}$ is considered as measurement error. Notably, we bin labor productivity P across firms within a year into quantile bins. Across productivity-year bins, we can then estimate the parameter θ.

Using this calibration strategy, we can recast the two equilibrium equations 7 and 8 as (cf. Appendix section A.1.9 for derivation)

$$\frac{\gamma}{\theta} = UE\frac{k_{\Phi}}{k_{\Theta}} + EE + \beta\alpha_{\Upsilon}\frac{k_{\Phi}}{k_{\Theta}} + \delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right) + (UE - \delta)\frac{(1-u)}{f}$$

$$\frac{\gamma}{\theta} = \frac{(1-u)}{uf}\left(\delta\frac{k_{\Theta}}{k_{\Phi}} - \frac{((UE-\delta)\alpha_{\Pi} + UE)}{u}\right).$$

We can see that this equation relates parameter estimates to the growth rate γ, the unemployment rate u and the relative efficiencies of innovation sources α_{Π} and α_{Υ}. Next, we will discuss calibration estimates and conclusions we can draw about the relative importance of innovative sources for productivity.

5.2 Model estimates and Growth Decomposition

Parameter estimates We summarize the set of estimated parameters in Appendix Table A.8. While the estimated labor market parameters are rather standard, the innovation parameters α, θ and β are a novel feature of our theory. We first discuss estimates for the productivity penalty α and the innovation tail parameter θ. In our estimates, we find that firms' productivity declines on average by 3% when loosing a worker such that $\alpha = 0.97$. In comparison, Sauvagnat and Schivardi (2023) report a drop in ROA of 2.1% after the death of an executive in thin labor markets and of 0.8% in thick labor markets which is quantitatively comparable to our results.

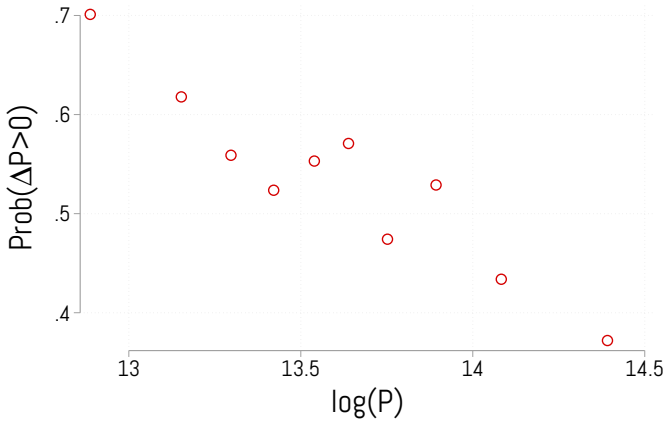


Figure 8: Parameter estimates

Notes: The figure shows the likelihood of firm productivity increases for a new hire event. Estimation is performed across year-specific bins of firm productivity. The corresponding estimation equation is $\log E\left[\text{Prob}\{\Delta P > 0\}\right]_{n,t} = c_0 - 1/\theta\left(\log P_{n,t} - \gamma t\right) + u_{n,t}$. We exclude all observations where more than 10 percent of workers leave for unemployment.

Figure 8 contains a graphical representation of the estimation results for the productivity distribution parameter θ. We find a scale parameter of the Pareto distribution θ of 0.76. We can compare our estimate for the tail Parameter θ to values used in Lucas and Moll (2014) who consider values between 0.5 and 0.8 for the US economy. We find $\beta = 0.02$, such that (after controlling for observables), we expect a small share of firms to perform innovation. While this number is low, the literature has long noted that there is a large share of firms without R&D expenditures (Klette and Kortum, 2004).

Given these parameter estimates, we can analyze the implied relationship between the relative productivity distribution parameters $\frac{k_\Phi}{k_\Theta}$, and the relative innovation intensities of innovation α_Υ and labor market entry α_Π. We illustrate this relationship in Figure A.8 in the Appendix.[22] The figure illustrates the economically relevant range of the parameter $\frac{k_\Phi}{k_\Theta}$ such that $\alpha_\Upsilon > 0$ and $\alpha_\Pi > 0$. Over this range, it is mostly the case that $\alpha_\Upsilon > \alpha_\Pi$, such that the distribution of new ideas has a higher mean than the distribution of skills of new labor

[22]We here make use of the mapping

$$\alpha_\Upsilon = \frac{\left(\frac{\gamma}{\theta} - UE\frac{k_\Phi}{k_\Theta} - EE - \delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right) - (UE - \delta)\frac{(1-u)}{f}\right)}{\beta\frac{k_\Phi}{k_\Theta}}$$

$$\alpha_\Pi = \frac{\delta\frac{k_\Theta u}{k_\Phi} - \frac{\gamma u^2 f}{\theta(1-u)} - UE}{(UE - \delta)}$$

market entrants, as expected.

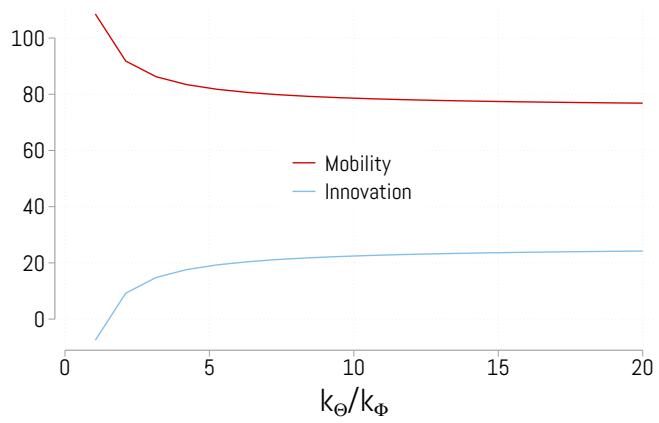
Growth Decomposition Using these estimates, we can decompose economic growth into four parts: worker mobility, innovation, new firm arrival and worker displacement, as shown in equation 9.

$$\gamma = \overbrace{\theta UE\frac{k_\Phi}{k_\Theta} + \theta EE}^{\text{Mobility}} + \overbrace{\theta\beta\alpha_\Upsilon\frac{k_\Phi}{k_\Theta}}^{\text{Innovation}} + \overbrace{\theta\delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right)}^{\text{Displacement}} + \overbrace{\theta(UE-\delta)\frac{(1-u)}{f}}^{\text{New Firms}} \tag{9}$$

All else equal, our parameter estimates show that a drop in the EE firm mobility rate by 10% (by 0.003) affects output growth by 0.00183 percentage points (or 6% of the estimated aggregate average growth rate). These growth shares depend on the relative productivity distribution parameters $\frac{k_\Phi}{k_\Theta}$. However, quantitatively, we find that the growth decomposition does not vary much with these estimates over the economically relevant range , as we show in Figure 9.

Overall, we find that worker mobility accounts with over 70% for the majority of economic growth, and that mobility and innovation account for the large majority of the contribution to growth. The first result finds resonance in Liu (2023). While featuring a different setting, Liu (2023) reports that worker mobility accounts for 61.3% of TPF growth. In appendix section A.2 we show how changes to the parameter space effect this growth share. There we show that a larger tail of the firm productivity distribution $1/\theta$ lowers the importance of worker mobility for growth. We conclude that in the range of values considered by Lucas and Moll (2014), the growth contribution is at least 50%. We can further compare our findings to our empirical analysis through a variance decomposition of labor productivity growth across sectors. This analysis is shown in Table 4. At the cross-section of sectors, we find that the majority of productivity growth is accounted for by worker mobility and this especially so when considering worker mobility among the top ten percent of the income distribution. These results further lend support to our findings.

Figure 9: Growth Decomposition



Notes: The figure shows a graphical representation of the the growth share due to worker mobility or innovation given $\frac{k_\Phi}{k_\Theta}$ together with the rest of the parameters space.

	Category of occupations	
	Bottom half	Top ten percent
Dep. var: productivity growth	(1)	(2)
Factor		
EE mobility	0.021**	0.132***
	(48%)	(69%)
R&D	0.008	0.057***
	(18%)	(30%)
Covariance	0.015*	0.002
	(34%)	(1%)
Sum	0.044*	0.191***

Notes: The table contains estimates of a variance composition of residual productivity growth on EE mobility, R&D and the covariance between these two factors. Residualization has been performed with respect to productivity, trade-shocks and firm size. Estimates in parentheses denote shares in percent. * denotes a p-value of less than 10 percent, ** less than 5 percent, and *** less than 1 percent.

Table 4: Share of variation in productivity growth explained by mobility versus innovation.

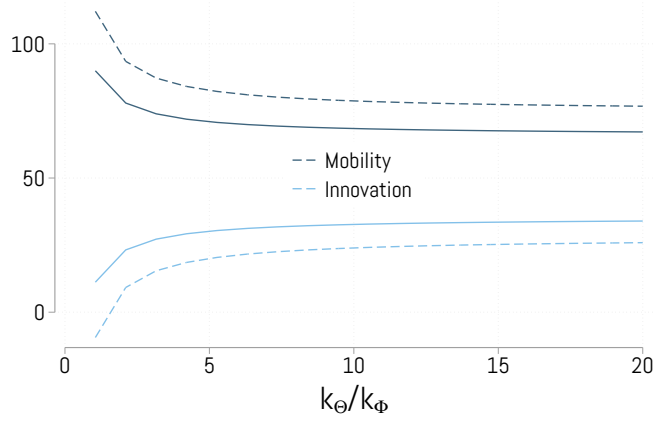
5.3 Sub-sample Analysis

We now consider an application of our framework to the discussion of recent changes in economic growth determinants. A significant literature has documented a decline in rates of job creation and job destruction (Davis and Haltiwanger, 2014; Decker et al., 2016) and job-to-job mobility (Baksy et al., 2024; Hyatt and Spletzer, 2016; Fujita et al., forthcoming)

for the U.S. economy. Simultaneously, the literature has discussed a relative decline in R&D spending devoted to innovation - despite increases in research expenditures overall (Arora et al., 2020). While these facts have been observed above all for the U.S. economy, we find evidence for a small decline in our estimates of job-to-job hiring rate at the firm level over our sample period in Sweden, cf. Figure A.9 in the Appendix. Note that this estimate is constructed at the firm level, whereas the literature usually documents the job mobility level at the worker level.

We take this as motivation to undertake a sub-sample analysis with split year 2009, yielding a half sample split. Parameter estimates for the two samples are collected in Table A.9 in the Appendix. We find that labor market mobility has slightly decreased whereas innovation intensity increased in our Swedish data. At the same time, estimates for the tail parameter θ and overall growth γ are found to be higher in the post as compared to the pre-period. Figure 10 shows that these estimates imply that labor mobility had less impact on aggregate growth in Sweden after 2009. Nevertheless, labor mobility accounts for the majority of economic growth over both sample periods.

Figure 10: Growth Decomposition - Sub-sample Analysis



Notes: The figure shows a graphical representation of the growth share due to worker mobility or innovation given $\frac{k_\Phi}{k_\Theta}$ together with the rest of the parameters space. The dashed line represents the decomposition for the period before 2009 whereas the solid line represents estimates after 2009.

6 Conclusion

In this paper, we have shown empirically and theoretically grounded evidence that worker mobility affects firm growth. We have proceeded two-fold with our analysis. First, using highly granular data for workers and firms in Sweden, we provide aggregate and microeconomic evidence for the correlation of worker mobility and growth in labor productivity, both for horizontal and vertical productivity growth. At the aggregate level, we find suggestive evidence that both worker mobility as well as R&D shape firm productivity growth. Second, we develop a random search model on a balanced growth path to estimate the relative impact of worker mobility and R&D for aggregate productivity growth. As in our empirical evidence, we find that both channels matter for growth. Crucially — and intuitively — the rate of worker mobility conditions the efficiency of worker mobility for aggregate growth.

Our results have important implications for understanding productivity growth, especially in light of decreasing mobility of workers across space and firms in recent decades and differences in worker mobility across countries. All else equal, our model predicts falling aggregate productivity growth in the presence of reduced worker mobility. This has important implications for policy makers. In fact, employment protection legislation that reduces labor mobility can therefore have an aggregate effect on labor productivity, even beyond their effect on firm incentives for R&D as studied in Aghion et al. (2023).

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Appendix A Online Appendix

The following online appendix assembles details for the derivations in the theoretical section (cf. section A.1), details on a sensitivity analysis (cf. section A.2) as well as additional details on the data set (cf. section A.3), empirical evidence (cf. section A.4) and estimation results (cf. section A.5).

A.1 Derivations

A.1.1 Derivation Continuous Time Bellman Equation Joint Value

Time is indexed by $t, t+\Delta, ...$ The discount factor between two periods is denoted as $(1-\Delta r)$. The discrete time Bellman equation is

$$\begin{aligned}
&\Omega(P,N,t) = \Delta Y(P,N,t) + (1-\Delta r)[\\
&(EU \text{ Mobility}) + \Delta\delta\left(U(t+\Delta) + \Omega(\tilde{P}, N-1, t+\Delta)\right) \\
&(UE \text{ Mobility}) + (1-\Delta\delta)\Delta\lambda\left(\int_P^{\infty}\Omega(P', N+1, t+\Delta)dF(P',t) + \int_{\underline{P}}^{P}\Omega(P, N+1, t+\Delta)dF(P',t)\right) \\
&\qquad - (1-\Delta\delta)\Delta\lambda U(t+\Delta) \\
&(\text{Innovation}) + (1-\Delta\delta)(1-\Delta\lambda)\Delta\beta\left(\int_P^{\infty}\Omega(P', N, t+\Delta)dV(P,t) + \int_{\underline{P}}^{P}\Omega(P, N, t+\Delta)dV(P,t)\right) \\
&(\text{No change}) + (1-\Delta\delta)(1-\Delta\lambda)(1-\Delta\beta)\Omega(P,N,t+\Delta)] \qquad (10)
\end{aligned}$$

where $\tilde{P} = \alpha P$. Note that

$$\begin{aligned}
\Omega(P', N+1, t+\Delta) &= \Omega(P', N+1, t+\Delta) - \Omega(P, N+1, t+\Delta) \\
&\quad + \Omega(P, N+1, t+\Delta) - \Omega(P, N, t+\Delta) \\
&\quad + \Omega(P, N, t+\Delta) \\
\Omega(P, N+1, t+\Delta) &= \Omega(P, N+1, t+\Delta) - \Omega(P, N, t+\Delta) + \Omega(P, N, t+\Delta) \\
\Omega(\tilde{P}, N-1, t+\Delta) &= \Omega(\tilde{P}, N-1, t+\Delta) - \Omega(P, N-1, t+\Delta) \\
&\quad + \Omega(P, N-1, t+\Delta) - \Omega(P, N, t+\Delta) + \Omega(P, N, t+\Delta)
\end{aligned}$$

Using the substitutions $\Omega_{N+1} := \Omega(P, N+1, t+\Delta) - \Omega(P, N, t+\Delta)$, $\Omega_{t+\Delta} := \Omega(P, N, t+\Delta) - \Omega(P, N, t)$ and $\Omega_{P',P,N} := \Omega(P', N, t+\Delta) - \Omega(P, N, t+\Delta)$, we can rewrite

$$\begin{aligned}
\Omega(P', N+1, t+\Delta) - \Omega(P, N, t) &= \Omega_{P',P,N+1} + \Omega_{N+1} + \Omega_{t+\Delta} \\
\Omega(P, N+1, t+\Delta) - \Omega(P, N, t) &= \Omega_{N+1} + \Omega_{t+\Delta} \\
\Omega(\tilde{P}, N-1, t+\Delta) &= \Omega_{\tilde{P},P,N-1} + \Omega_{N-1} + \Omega_{t+\Delta}
\end{aligned}$$

We subtract $(1-\Delta r)\Omega(P,N,t)$ from both sides of equation 10 and use the substitutions, yielding

$$\begin{aligned}
\Delta r\Omega(P,N,t) &= \Delta Y(P,N,t) + (1-\Delta r)[\\
(EU \text{ Mobility}) &+ \Delta\delta\left(U(t+\Delta) + \Omega_{\tilde{P},P,N-1} + \Omega_{N-1} + \Omega_{t+\Delta}\right) \\
(UE \text{ Mobility}) &+ (1-\Delta\delta)\Delta\lambda\left(\Omega_{N+1} - U(t+\Delta) + \Omega_{t+\Delta}\right) \\
&+ (1-\Delta\delta)\Delta\lambda\left(\int_P^\infty \Omega_{P',P,N+1}dF(P',t)\right) \\
(\text{Innovation}) &+ (1-\Delta\delta)(1-\Delta\lambda)\Delta\beta\left(\int_P^\infty \Omega_{P',P,N}dV(P',t) + \Omega_{t+\Delta}\right) \\
(\text{No change}) &+ (1-\Delta\delta)(1-\Delta\lambda)(1-\Delta\beta)\Omega_{t+\Delta}
\end{aligned}$$

We divide by Δ and take the limit when Δ goes to zero

$$\begin{aligned}
r\Omega(P,N,t) &= Y(P,N,t) + \Omega_t \\
(EU \text{ Mobility}) &+ \delta\left(U(t) + \Omega_{\tilde{P},P,N-1} + \Omega_{N-1}\right) \\
(UE \text{ Mobility}) &+ \lambda\left(\Omega_{N+1} - U(t) + \int_P^\infty \Omega_{P',P,N+1}dF(P',t)\right) \\
(\text{Innovation}) &+ \beta\int_P^\infty \Omega_{P',P,N}dV(P',t)
\end{aligned}$$

with $\Omega_t := \lim_{\Delta\to 0}\frac{\Omega(P,N,t+\Delta)-\Omega(P,N,t)}{\Delta}$. Note that we can similarly derive the value for an unemployed worker from the discrete-time value function

$$\begin{aligned}
U(t) &= b(t)\Delta + (1-\Delta r)\left(\Delta\lambda U(t+\Delta) + (1-\Delta\lambda)U(t+\Delta)\right) \\
&= b(t)\Delta + (1-\Delta r)U(t+\Delta)
\end{aligned}$$

we subtract $(1-\Delta r)U(t)$ and take the limit, yielding

$$rU(t) = b(t) + U_t$$

with $U_t := \lim_{\Delta\to 0}\frac{U(t+\Delta)-U(t)}{\Delta}$

A.1.2 Surplus representation

We aim at representing the joint value function in form of the surplus equation. To do this, we restart with the discrete time representation of the joint value equation, equation 10. Note that $\Omega(P,N,t) := S(P,N,t)+NU(t)$. We define the substitutions $S_N := S(P,N,t+\Delta)-S(P,N-1,t+\Delta)$, $S_{t+\Delta} := S(P,N,t+\Delta)-S(P,N,t)$, $S_{P',P,N} := S(P',N,t+\Delta)-S(P,N,t+\Delta)$, $U_{t+\Delta} = U(t+\Delta)-U(t)$ and rewrite the following expressions

$$
\begin{aligned}
\Omega(P',N+1,t+\Delta)-\Omega(P,N,t) &= S(P',N+1,t+\Delta)-S(P,N+1,t+\Delta)\\
&\quad + S(P,N+1,t+\Delta)-S(P,N,t+\Delta)\\
&\quad + S(P,N,t+\Delta)+(N+1)U(t+\Delta)\\
&\quad - S(P,N,t)-NU(t)\\
&= S_{P',P,N+1}+S_{N+1}+S_{t+\Delta}+NU_{t+\Delta}+U(t+\Delta)\\
\Omega(P',N,t+\Delta)-\Omega(P,N,t) &= S(P',N,t+\Delta)-S(P,N,t+\Delta)\\
&\quad + S(P,N,t+\Delta)+NU(t+\Delta)-S(P,N,t)-NU(t)\\
&= S_{P',P,N}+S_{t+\Delta}+NU_{t+\Delta}\\
\Omega(P,N+1,t+\Delta)-\Omega(P,N,t) &= S(P,N+1,t+\Delta)-S(P,N,t+\Delta)+S(P,N,t+\Delta)\\
&\quad + (N+1)U(t+\Delta)-S(P,N,t)-NU(t)\\
&= S_{N+1}+S_{t+\Delta}+NU_{t+\Delta}+U(t+\Delta)\\
\Omega(\tilde{P},N-1,t+\Delta)-\Omega(P,N,t) &= S(\tilde{P},N-1,t+\Delta)-S(P,N-1,t+\Delta)\\
&\quad + S(P,N-1,t+\Delta)-S(P,N,t+\Delta)\\
&\quad + S(P,N,t+\Delta)+(N-1)U(t+\Delta)-S(P,N,t)-NU(t)\\
&= S_{\tilde{P},P,N-1}+S_{N-1}+S_{t+\Delta}+NU_{t+\Delta}-U(t+\Delta)
\end{aligned}
$$

We subtract $(1-\Delta r)\Omega(P,N,t)$ from both sides of equation 10 and use the substitutions, yielding

$$\begin{aligned}\Delta r(S(P,N,t)+NU(t)) &= \Delta Y(P,N,t)+(1-\Delta r)[\\ &(EU \text{ Mobility})+\Delta\delta\left(S_{\tilde{P},P,N-1}+S_{N-1}+S_{t+\Delta}+NU_{t+\Delta}\right)\\ &(UE \text{ Mobility})+(1-\Delta\delta)\Delta\lambda\left(S_{N+1}+S_{t+\Delta}+NU_{t+\Delta}+\int_P^\infty S_{P',P,N+1}dF(P',t)\right)\\ &(\text{Innovation})+(1-\Delta\delta)(1-\Delta\lambda)\Delta\beta\left(S_{t+\Delta}+NU_{t+\Delta}+\int_P^\infty S_{P',P,N}dV(P',t)\right)\\ &(\text{No change})+(1-\Delta\delta)(1-\Delta\lambda)(1-\Delta\beta)\left(S_{t+\Delta}+NU_{t+\Delta}\right)]\end{aligned}$$

We divide by Δ and take the limit when Δ goes to zero. We also use the equation for the value of unemployment and denote $R(P,N,t)=(P-b(t))N$

$$\begin{aligned}rS(P,N,t) &= R(P,N,t)+S_t\\ &(EU \text{ Mobility})+\delta\left(S_{\tilde{P},P,N-1}+S_{N-1}\right)\\ &(UE \text{ Mobility})+\lambda\left(S_{N+1}+\int_P^\infty S_{P',P,N+1}dF(P',t)\right)\\ &(\text{Innovation})+\beta\int_P^\infty S_{P',P,N}dV(P',t)]\end{aligned}$$

with $S_t := \lim_{\Delta\to 0}\frac{S(P,N,t+\Delta)-S(P,N,t)}{\Delta}$

A.1.3 Affine surplus representation

We will proceed by guess and verify. We guess the affine surplus representation $S(P,N,t) = N\hat{S}(P,t) + S^0(P,t)$ for the surplus equation

$$\begin{aligned} rS(P,N,t) = R(P,N,t) + S_t + (\lambda - \delta)\, S_N + \delta S_{\tilde{P},P,N-1} \\ + \lambda \int_P^\infty S_{P',P,N+1} dF(P',t) + \beta \int_P^\infty S_{P',P,N} dV(P',t) \end{aligned} \tag{11}$$

Using the guess, define and express the following short-hands

$$\begin{aligned} S_N &:= S(P,N,t) - S(P,N-1,t) = \hat{S}(P,t) = S_{N+1} = -S_{N-1} \\ S_t &:= \lim_{\Delta \to 0} \frac{S(P,N,t+\Delta) - S(P,N,t)}{\Delta} = N\hat{S}_t(P,t) + S^0_t(P,t) \\ S_{P',P,N} &:= S(P',N,t+\Delta) - S(P,N,t+\Delta) = N\hat{S}_{P',P}(P,t) + S^0_{P',P}(P,t) \end{aligned}$$

with the corresponding substitutions $\hat{S}_t := \lim_{\Delta\to 0} \frac{\hat{S}(P,t+\Delta) - \hat{S}(P,t)}{\Delta}$, $\hat{S}_{P',P} := \hat{S}(P',t) - \hat{S}(P,t)$, $S^0_t := \lim_{\Delta\to 0} \frac{S^0(P,t+\Delta) - S^0(P,t)}{\Delta}$, $S^0_{P',P} := S^0(P',t) - S^0(P,t)$. Note in particular that $S_{N+1} = -S_{N-1}$. We verify the initial guess by using the differenced surplus equation ($rS(P,N,t) - rS(P,N-1,t)$) to obtain the implicit equations that define $\hat{S}(P,t)$ and $S^0(P,t)$. From

$$rS(P,N,t) - rS(P,N-1,t) = rS_N = r\hat{S}(P,t)$$

we obtain

$$r\hat{S}(P,t) = (P - b(t)) + \hat{S}_t(P,t) + \delta \hat{S}_{\tilde{P},P} + \lambda \int_P^\infty \hat{S}_{P',P} dF(P',t) + \beta \int_P^\infty \hat{S}_{P',P} dV(P',t)$$

Using the surplus equation 11, we now back out the equation defining $S^0(P,t)$

$$\begin{aligned} rN\hat{S}(P,t) + rS^0(P,t) &= N\left((P - b(t)) + \hat{S}_t(P,t)\right) \\ &\quad + N\left(\delta \hat{S}_{\tilde{P},P} + \lambda \int_P^\infty \hat{S}_{P',P} dF(P',t) + \beta \int_P^\infty \hat{S}_{P',P} dV(P',t)\right) + rS^0(P,t) \\ &= R(P,N,t) + S_t + (\lambda - \delta)\, S_N + \delta S_{\tilde{P},P,N-1} \\ &\quad + \lambda \int_P^\infty S_{P',P,N+1} dF(P',t) + \beta \int_P^\infty S_{P',P,N} dV(P',t) \end{aligned}$$

Hence,

$$rS^0(P,t) = S_t^0(P,t) + (\lambda - \delta)\,\hat{S}(P,t) + \delta\left(S^0_{\tilde{P},P} - \hat{S}_{\tilde{P},P}\right) + \lambda\int_P^\infty \left(\hat{S}_{P',P} + S^0_{P',P}\right) dF(P',t) + \beta\int_P^\infty S^0_{P',P} dV(P',t)$$

A.1.4 Derivations Distributions Balanced Growth Path

To show that we can represent the surplus function on the balanced growth path, we rewrite the equation

$$\begin{aligned} rS(P,N,t) = R(P,N,t) + S_t + (\lambda - \delta)\, S_N + \delta S_{\tilde{P},P,N-1} \\ + \lambda \int_P^\infty S_{P',P,N+1} dF(P',t) + \beta \int_P^\infty S_{P',P,N} dV(P',t) \end{aligned}$$

On the BGP, where

$$\begin{aligned} F(P,t) &= \Phi(Pe^{-\gamma t}) \\ G(P,t) &= \Theta(Pe^{-\gamma t}) \\ V(P,t) &= \Upsilon(Pe^{-\gamma t}) \\ S(P,N,t) &= e^{\gamma t}\sigma(Pe^{-\gamma t}, N) \\ &= e^{\gamma t}\left(N\hat{\sigma}(Pe^{-\gamma t}) + \sigma^0(Pe^{-\gamma t})\right) \\ f(P,t) &= e^{-\gamma t}\Phi'(Pe^{-\gamma t}) \\ v(P,t) &= e^{-\gamma t}\Upsilon'(Pe^{-\gamma t}) \\ b(t) &= e^{\gamma t} b \end{aligned}$$

such that

$$\begin{aligned} S_N &:= S(P,N,t) - S(P,N-1,t) = e^{\gamma t}\left(\sigma(Pe^{-\gamma t}, N) - \sigma(Pe^{-\gamma t}, N-1)\right) := e^{\gamma t}\sigma_N \\ S_t &:= \lim \frac{S(P,N,t+\Delta) - S(P,N,t)}{\Delta} = e^{\gamma t}\left(\lim \frac{\sigma(Pe^{-\gamma t+\Delta}, N) - \sigma(Pe^{-\gamma t}, N)}{\Delta}\right) \\ &:= e^{\gamma t}\sigma_t \\ S_{\tilde{P},P,N-1} &:= S(\tilde{P}, N-1, t) - S(P, N-1) = e^{\gamma t}\left(\sigma(\tilde{P}e^{-\gamma t}, N-1) - \sigma(Pe^{-\gamma t}, N-1)\right) \\ &:= e^{\gamma t}\sigma_{\tilde{P},P,N-1} \\ S_{P',P,N} &:= S(P',N,t) - S(P,N,t) = e^{\gamma t}\left(\sigma(P'e^{-\gamma t}, N) - \sigma(Pe^{-\gamma t}, N)\right) \end{aligned}$$

Plugging into the surplus equation and making the substitution $x = Pe^{-\gamma t}$

$$rS(P,N,t) = R(P,N,t) + S_t + (\lambda - \delta)\, S_N + \delta S_{\tilde{P},P,N-1} \\ + \lambda \int_P^\infty S_{P',P,N+1} dF(P',t) + \beta \int_P^\infty S_{P',P,N} dV(P',t)$$

such that

$$re^{\gamma t}\sigma(Pe^{-\gamma t},N) = (x-b)e^{\gamma t}N + e^{\gamma t}\sigma_t + (\lambda-\delta)\, e^{\gamma t}\sigma_N + \delta e^{\gamma t}\sigma_{\tilde{x},x,N-1} \\ + \lambda \int_P^\infty e^{\gamma t}\sigma_{x',x,N+1} e^{-\gamma t}\Phi'(x)dx e^{\gamma t} + \beta \int_P^\infty e^{\gamma t}\sigma_{x',x,N} e^{-\gamma t}\Upsilon'(x)dx e^{\gamma t}$$

With simplification, yielding

$$r\sigma(x,N) = (x-b)N + \sigma_t + (\lambda-\delta)\, \sigma_N + \delta\sigma_{\tilde{x},x,N-1} \\ + \lambda \int_P^\infty \sigma_{x',x,N+1}\Phi'(x)dx + \beta \int_P^\infty \sigma_{x',x,N}\Upsilon'(x)dx$$

We hence find the surplus equation independent of time.

A.1.5 Derivations Distributions Balanced Growth Path

Using the balanced growth path distributions such that

$$\frac{\partial f(P,t)}{\partial t} = -\gamma e^{-\gamma t}\Phi'(ze^{-\gamma t}) - z\gamma(e^{-\gamma t})^2\Phi''(ze^{-\gamma t})$$
$$\frac{\partial g(P,t)}{\partial t} = -\gamma e^{-\gamma t}\Theta'(ze^{-\gamma t}) - z\gamma(e^{-\gamma t})^2\Theta''(ze^{-\gamma t})$$

we can derive the productivity distribution of the unemployed workers and the distribution of firms.

Distribution of the unemployed Starting from the equation for the change in the distribution of the unemployed

$$\delta g(P,t)\eta_p + \mu_w w(P,t)\frac{1}{u} - \lambda f(P,t)\eta_{IJ} = \frac{\partial f(P,t)}{\partial t}$$

where $\eta_{IJ} = \frac{N_t^J}{u_t N_t^I}$ we obtain by plugging in

$$e^{-\gamma t}\left(\delta\Theta'(ze^{-\gamma t})\eta_p + \frac{\mu_w}{u}\Pi'(ze^{-\gamma t}) - \lambda\Phi'(ze^{-\gamma t})\eta_p\right) = e^{-\gamma t}\left(-\gamma\Phi'(ze^{-\gamma t}) - z\gamma(e^{-\gamma t})\Phi''(ze^{-\gamma t})\right)$$

$$\lambda - \delta\frac{\Theta'(ze^{-\gamma t})}{\Phi'(ze^{-\gamma t})} + \frac{\mu_w}{N^J/N^I}\frac{\Pi'(ze^{-\gamma t})}{\Phi'(ze^{-\gamma t})} = \frac{1}{\eta_{IJ}}\gamma\left(1 + \frac{z(e^{-\gamma t})\Phi''(ze^{-\gamma t})}{\Phi'(ze^{-\gamma t})}\right)$$

Using $x = ze^{-\gamma t}$

$$\frac{\lambda}{\delta} - \frac{\gamma/\eta_{IJ}}{\delta}\left(1 + \frac{x\Phi''(x)}{\Phi'(x)}\right) = \frac{\Theta'(x)}{\Phi'(x)} - \frac{\mu_w}{\delta}\frac{N^I}{N^J}\frac{\Pi'(x)}{\Phi'(x)}$$

Leveraging assumptions 1 and 2, we take the limit such that $\lim_{x\to\infty}\frac{x\Phi''(x)}{\Phi'(x)} = -\frac{(\theta+1)}{\theta}$. We also use that $\lim_{x\to\infty}\frac{\Theta'(x)}{\Phi'(x)} = \frac{k_\Theta}{k_\Phi}$ and $\lim_{x\to\infty}\frac{\Pi'(x)}{\Phi'(x)} = \alpha_\Pi$ We obtain

$$\frac{(\lambda + \frac{\gamma}{\eta_p\theta})}{\delta} = \frac{k_\Theta}{k_\Phi} - \frac{\mu_w}{\delta}\frac{N_0^I}{N_0^J}\alpha_\Pi$$

Distribution of firm productivity From

$$\lambda\left(f(P,t)G(P,t)-g(P,t)\bar{F}(P,t)\right)+\beta\left(v(P,t)G(P,t)-g(P,t)\bar{V}(P,t)\right)+$$
$$\mu_f g(P,t)+\delta\left(g(P/\alpha,t)-g(P,t)\right)=\frac{\partial g(P,t)}{\partial t}$$

we obtain by plugging in

$$\begin{aligned}
&e^{-\gamma t}\lambda\left(\Phi'(ze^{-\gamma t})\Theta(ze^{-\gamma t})-\Theta'(ze^{-\gamma t})(1-\Phi(ze^{-\gamma t}))\right)+\\
&e^{-\gamma t}\beta\left(\Upsilon'(ze^{-\gamma t})\Theta(ze^{-\gamma t})-\Theta'(ze^{-\gamma t})(1-V(ze^{-\gamma t})\right)+\\
&+e^{-\gamma t}\left(\mu_f\Theta'(ze^{-\gamma t})+\delta\left(\frac{1}{\alpha}\Theta'\left(z/\alpha e^{-\gamma t}\right)-\Theta'(ze^{-\gamma t})\right)\right)\\
&=e^{-\gamma t}\left(-\gamma\Theta'(ze^{-\gamma t})-z\gamma(e^{-\gamma t})\Theta''(ze^{-\gamma t})\right)
\end{aligned}$$

we express using $x=ze^{-\gamma t}$ and simplify

$$\begin{aligned}
&\lambda\left(\frac{\Phi'(x)}{\Theta'(x)}\Theta(x)-(1-\Phi(x))\right)+\beta\left(\frac{\Upsilon'(x)}{\Theta'(x)}\Theta(x)-(1-V(x)\right)+\\
&+\left(\mu_f+\delta\left(\frac{\frac{1}{\alpha}\Theta'\left(x/\alpha\right)}{\Theta'(x)}-1\right)\right)=-\gamma\left(1+\frac{x\Theta''(x)}{\Theta'(x)}\right)
\end{aligned}$$

We take limit, using $\lim_{x\to\infty}\frac{x\Phi''(x)}{\Phi'(x)}=-\frac{(\theta+1)}{\theta}$, $\lim_{x\to\infty}\frac{\frac{1}{\alpha}\Theta'(x/\alpha)}{\Theta'(x)}=\alpha^{\frac{1-\theta}{\theta}}-1$. We also use that $\lim_{x\to\infty}\frac{\Theta'(x)}{\Phi'(x)}=\frac{k_\Theta}{k_\Phi}$ and $\lim_{x\to\infty}\frac{\Upsilon'(x)}{\Theta'(x)}=\alpha_\Upsilon\frac{k_\Phi}{k_\Theta}$

$$\lambda\frac{k_\Phi}{k_\Theta}+\beta\alpha_\Upsilon\frac{k_\Phi}{k_\Theta}+\mu_f+\delta\left(\alpha^{\frac{1-\theta}{\theta}}-1\right)=\gamma/\theta$$

A.1.6 Joint Value Function with Job-to-Job Mobility

In addition to the previous events discussed for the setting without job-to-job mobility, a firm experiences two more events, a EE Hire or an EE Exit.

- (EE Hire): The firm experiences the chance of meeting an employed worker at rate $s\lambda(1-u)$. If the worker is of higher productivity than the firm, the joint firm value increases to $\int_{P}^{\infty}\Omega(P',N+1,t+\Delta)dG(P',t)$, if the worker is not as productive, the value increases to $\int_{\underline{P}}^{P}\Omega(P,N+1,t+\Delta)dG(P',t)$. The worker firm coalition further sees drop in the value contribution at the sending firm of size $\int_{\underline{P}}^{\infty}\Omega(P',N'+1,t+\Delta)-\Omega(P',N',t+\Delta)dG(P',t)$, which is the value that the origin firm would we willing to pay to prevent the worker from leaving. Note that we are using the guess and verify approach such that $\Omega(P',N'+1,t+\Delta)-\Omega(P',N',t+\Delta)$ is independent of the sending firm size.

- (EE Exit): The firm has the chance that one of its workers is contacted by another firm at rate $\hat{\lambda}$. In that case, the firm does not experience a productivity disruption and keeps its value at $\Omega(P,N-1,t+\Delta)$, the worker keeps its productivity at P. At the new firm, the worker is offered the maximum marginal value that can be offered at the origin firm $\Omega(P,N,t+\Delta)-\Omega(P,N-1,t+\Delta)=\Omega_N(P,N,t)$. Hence, total value at the origin firm is changed to $\Omega(P,N,t+\Delta)$.

We can hence write the discrete time value function in an interval Δ as

$$
\begin{aligned}
\Omega(P,N,t) &= \Delta Y(P,N) + (1-\Delta r)[\\
(EU \text{ Mobility}) &+ \Delta\delta\left(U(P) + \Omega(\tilde{P},N-1,t+\Delta)\right) \\
(UE \text{ Mobility}) &+ (1-\Delta\delta)\Delta\lambda u\left(\int_{P}^{\infty}\Omega(P',N+1,t+\Delta)dF(P',t)\right) \\
&+ (1-\Delta\delta)\Delta\lambda u\left(\int_{\underline{P}}^{P}\Omega(P,N+1,t+\Delta)dF(P',t) - \int_{\underline{P}}^{\infty}U(P')dF(P',t)\right) \\
(EE \text{ Hire}) &+ (1-\Delta\delta)\Delta\lambda(1-u)\left(\int_{P}^{\infty}\Omega(P',N+1,t+\Delta)dG(P',t)\right) \\
&+ (1-\Delta\delta)\Delta\lambda(1-u)\left(\int_{\underline{P}}^{P}\Omega(P,N+1,t+\Delta)dG(P',t)\right) \\
&+ (1-\Delta\delta)\Delta\lambda(1-u)\left(-\int_{\underline{P}}^{\infty}\left(\Omega(P',N'+1,t+\Delta) - \Omega(P',N',t+\Delta)\right)dG(P',t)\right) \\
(EE \text{ Exit}) &+ (1-\Delta\delta)(1-\Delta\lambda)\Delta\hat{\lambda}\left(\Omega(P,N,t+\Delta)\right) \\
(\text{Innovation}) &+ (1-\Delta\delta)(1-\Delta\lambda)(1-\Delta\hat{\lambda})\Delta\beta\left(\int_{P}^{\infty}\Omega(P',N,t+\Delta)dV(P',t)\right) \\
&+ (1-\Delta\delta)(1-\Delta\lambda)(1-\Delta\hat{\lambda})\Delta\beta\left(\int_{\underline{P}}^{P}\Omega(P,N,t+\Delta)dV(P',t)\right) \\
(\text{No change}) &+ (1-\Delta\delta)(1-\Delta\lambda)(1-\Delta\hat{\lambda})(1-\Delta\beta)\Omega(P,N,t+\Delta)]
\end{aligned}
$$

where $\tilde{P} = \alpha P$ Using the same steps as in appendix section A.1.1 for the case without EE mobility, we obtain

$$
\begin{aligned}
r\Omega(P,N,t) &= Y(P,N,t) + \Omega_t \\
(EU \text{ Mobility}) &+ \delta\left(U(t) + \Omega_{\tilde{P},P,N-1} + \Omega_{N-1}\right) \\
(UE \text{ Mobility}) &+ \lambda u\left(\Omega_{N+1} - U(t) + \int_{P}^{\infty}\Omega_{P',P,N+1}dF(P',t)\right) \\
(EE \text{ Hire}) &+ \lambda(1-u)\left(\Omega_{N+1} + \int_{P}^{\infty}\Omega_{P',P,N+1}dG(P',t) - \int_{\underline{P}}^{\infty}\Omega_{P',N'}dG(P',t)\right) \\
(\text{Innovation}) &+ \beta\int_{P}^{\infty}\Omega_{P',P,N}dV(P',t)
\end{aligned}
$$

where $\Omega_{P',N'} := \Omega(P',N'+1,t+\Delta) - \Omega(P',N',t+\Delta)$. We can compare this to the situation without EE mobility, and we find that we are having two additional terms due to EE Hires. Note also that the value function is independent of $\hat{\lambda}$ as mobility leaves the joint surplus

unaffected.

A.1.7 Affine surplus representation with with Job-to-Job Mobility

We will proceed by guess and verify. We guess the affine surplus representation $S(P,N,t) = N\hat{S}(P,t) + S^0(P,t)$ for the surplus equation

$$\begin{aligned}
rS(P,N,t) &= N\left(P - b(t)\right) + S_t \\
\text{(EU Mobility)} &+ \delta\left(-S_N + S_{\tilde{P},P,N-1}\right) \\
\text{(Mobility)} &+ \lambda\left(u_t\int_P^\infty S_{P',P,N+1}dF(P',t) + s(1-u_t)\int_P^\infty S_{P',P,N+1}dG(P',t)\right) \\
&+ \lambda\left(S_N - s(1-u_t)\int_{\underline{P}}^\infty S_{N'}(P',t)dF(P',t)\right) \\
\text{(Innovation)} &+ \beta\int_P^\infty S_{P',P,N}dV(P',t)
\end{aligned}$$

Using the guess, define and express the following short-hands

$$\begin{aligned}
S_N &:= S(P,N,t) - S(P,N-1,t) = \hat{S}(P,t) = S_{N+1} = -S_{N-1} \\
S_t &:= \lim_{\Delta\to 0}\frac{S(P,N,t+\Delta) - S(P,N,t)}{\Delta} = N\hat{S}_t(P,t) + S^0_t(P,t) \\
S_{P',P,N} &:= S(P',N,t+\Delta) - S(P,N,t+\Delta) = N\hat{S}_{P',P}(P,t) + S^0_{P',P}(P,t)
\end{aligned}$$

with the corresponding substitutions $\hat{S}_t := \lim_{\Delta\to 0}\frac{\hat{S}(P,t+\Delta)-\hat{S}(P,t)}{\Delta}$, $\hat{S}_{P',P} := \hat{S}(P',t) - \hat{S}(P,t)$, $S^0_t := \lim_{\Delta\to 0}\frac{S^0(P,t+\Delta)-S^0(P,t)}{\Delta}$, $S^0_{P',P} := S^0(P',t) - S^0(P,t)$. Note in particular that $S_{N+1} = -S_{N-1}$. We verify the initial guess by using the differenced surplus equation $(rS(P,N,t) - rS(P,N-1,t))$ to obtain the implicit equations that define $\hat{S}(P,t)$ and $S^0(P,t)$. From

$$rS(P,N,t) - rS(P,N-1,t) = rS_N = r\hat{S}(P,t)$$

we obtain

$$\begin{aligned}
r\hat{S}(P,t) = \left(P - b(t)\right) &+ \hat{S}_t(P,t) + \delta\hat{S}_{\tilde{P},P} + \beta\int_P^\infty \hat{S}_{P',P}dV(P',t) \\
&+ \lambda\left(u_t\int_P^\infty \hat{S}_{P',P}dF(P',t) + s(1-u_t)\int_P^\infty \hat{S}_{P',P}dG(P',t)\right)
\end{aligned}$$

Using the surplus equation 11, we now back out the equation defining $S^0(P,t)$

$$\begin{aligned}
rN\hat{S}(P,t) + rS^0(P,t) &= N\left((P - b(t)) + \hat{S}_t(P,t)\right) \\
&+ N\left(\delta \hat{S}_{\tilde{P},P} + \beta \int_P^\infty \hat{S}_{P',P} dV(P',t)\right) + rS^0(P,t) \\
&+ N\lambda\left(u_t \int_P^\infty \hat{S}_{P',P} dF(P',t) + s(1-u_t)\int_P^\infty \hat{S}_{P',P} dG(P',t)\right) \\
&= R(P,N,t) + S_t + (\lambda - \delta) S_N + \delta S_{\tilde{P},P,N-1} \\
&+ \beta \int_P^\infty S_{P',P,N} dV(P',t) \\
&+ \lambda\left(u_t \int_P^\infty S_{P',P,N+1} dF(P',t) + s(1-u_t)\int_P^\infty S_{P',P,N+1} dG(P',t)\right) \\
&+ \lambda\left(-s(1-u_t)\int_{\underline{P}}^\infty S_{N'}(P',t) dF(P',t)\right)
\end{aligned}$$

Hence,

$$\begin{aligned}
rS^0(P,t) &= S^0_t(P,t) + (\lambda - \delta)\hat{S}(P,t) + \delta\left(S^0_{\tilde{P},P} - \hat{S}_{\tilde{P},P}\right) + \beta\int_P^\infty S^0_{P',P} dV(P',t) \\
&+ \lambda u_t \int_P^\infty \left(\hat{S}_{P',P} + S^0_{P',P}\right) dF(P',t) \\
&+ \lambda s(1-u_t)\left(\int_P^\infty \left(\hat{S}_{P',P} + S^0_{P',P}\right) dG(P',t) - \int_{\underline{P}}^\infty \hat{S}(P',t) dG(P',t)\right)
\end{aligned}$$

A.1.8 Additional Equilibrium Relationships

In addition to the aforementioned equilibrium relationships, we note a set of additional restrictions. The first equates search intensity by workers and firms, such that

$$\tilde{\lambda} = \lambda \frac{N^J}{N^I}$$

The second restrictions derives from the equilibrium in the pool of unemployed workers. For a constant unemployment rate, the outflows from unemployment (as the mass of unemployed workers finding new employment, right hand side) and inflows (as the mass of new job market entrants and displaced workers, left hand side) have to balance, such that

$$\mu_I N^I + \delta N^J = u N^I \tilde{\lambda}$$

Hence, $\mu_I = (u\lambda - \delta)\frac{N^J}{N^I}$. Finally, for a constant average firm size $\frac{N^I u}{N^J}$, we require $\mu_f = \mu_I$.

A.1.9 Estimation Equations

Given the two equilibrium equations

$$\begin{aligned} \frac{\lambda + \frac{\gamma}{\eta_P \theta}}{\delta} &= \frac{k_\Theta}{k_\Phi} - \frac{\mu_w}{\delta}\frac{N^I}{N^J}\alpha_\Pi \\ \frac{\gamma}{\theta} &= \lambda\left(\frac{k_\Phi}{k_\Theta}u + (1-u)s\right) + \beta\alpha_\Upsilon \frac{k_\Phi}{k_\Theta} + \mu_f + \delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right) \end{aligned}$$

and the relations $\mu_f = (\lambda u - \delta)\frac{N^J}{N^I} = \mu_I$, $\eta_P = \frac{N^J}{uN^I}$, $\mu_w = \frac{\mu_f}{u}$, we rewrite the first equation as

$$\begin{aligned} \frac{\gamma}{\eta_P \theta} &= \delta\frac{k_\Theta}{k_\Phi} - \lambda - \frac{\mu_f}{u}\frac{N^I}{N^J}\alpha_\Pi \\ \frac{\gamma}{\theta} &= \frac{N^J}{uN^I}\left(\delta\frac{k_\Theta}{k_\Phi} - \lambda - \frac{(\lambda u - \delta)}{u}\alpha_\Pi\right) \end{aligned}$$

We rewrite the second equation as

$$\frac{\gamma}{\theta} = u\lambda\frac{k_\Phi}{k_\Theta} + (1-u)s\lambda + \beta\alpha_\Upsilon\frac{k_\Phi}{k_\Theta} + \delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right) + (\lambda u - \delta)\frac{N^J}{N^I}$$

We observe the following mapping to estimated quantities

- probability of new hire from employment: $(1-u)s\lambda = EE$
- probability of new hire from unemployment $u\lambda = UE$
- average firm size $\frac{(1-u)N^I}{N^J} = f$
- estimates of $\frac{k_\Phi}{k_\Theta}$, $\beta\alpha_\Upsilon\frac{k_\Phi}{k_\Theta}$, $\delta\left(\alpha^{\frac{1-\theta}{\theta}}-1\right)$, δ

Using these short hands,

$$\begin{aligned}\frac{\gamma}{\theta} &= UE\frac{k_\Phi}{k_\Theta} + EE + \beta\alpha_\Upsilon\frac{k_\Phi}{k_\Theta} + \delta\left(\alpha^{\frac{1-\theta}{\theta}}-1\right) + (UE-\delta)\frac{(1-u)}{f}\\ \frac{\gamma}{\theta} &= \frac{(1-u)}{uf}\left(\delta\frac{k_\Theta}{k_\Phi} - \frac{((UE-\delta)\alpha_\Pi + UE)}{u}\right)\end{aligned}$$

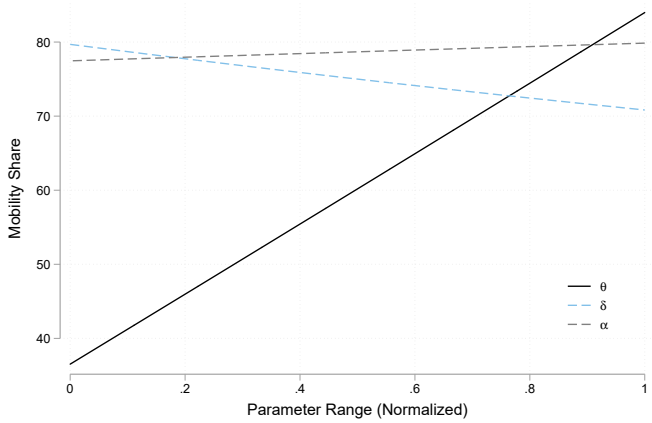
From these equations, we find relative efficiencies $\alpha_\Upsilon, \alpha_\Pi$ as

$$\begin{aligned}\alpha_\Upsilon &= \frac{\left(\frac{\gamma}{\theta} - UE\frac{k_\Phi}{k_\Theta} - EE - \delta\left(\alpha^{\frac{1-\theta}{\theta}}-1\right) - (UE-\delta)\frac{(1-u)}{f}\right)}{\beta\frac{k_\Phi}{k_\Theta}}\\ \alpha_\Pi &= \frac{\delta\frac{k_\Theta u}{k_\Phi} - \frac{\gamma u^2 f}{\theta(1-u)} - UE}{(UE-\delta)}\end{aligned}$$

A.2 Sensitivity Analaysis

To understand the driving factors of the share of growth deriving from mobility, we calculate the mobility share when varying one of the parameters while keeping the others fixed. These results are shown graphically in Figure A.1. In the figure, we vary the parameters θ, α and δ over a range of values for the parameter in question while keeping all other values set. For the normalized value of the parameters, we then represent the average growth share due to mobility. Intuitively, a higher displacement probability δ or skill depreciation upon

Figure A.1: Growth Share across Parameter Variations



Notes: The figure shows the average share of growth due to mobility, over the range of $\frac{k_\Phi}{k_\Theta}$ when varying one parameter at the time, from θ:[0.3 0.8], δ and α:[0.001 0.2], with a normalization on the unit line.

displacement $1-\alpha$ reduces the contribution to growth emanating from worker mobility. At the same time, the tail parameter of the productivity distribution is most impactful such that the importance of worker mobility increases in θ. Recall that $1/\theta$ is the tail parameter of the Pareto distribution describing the firm productivity distribution. Hence, the larger the tail parameter, the lower the growth contribution from workers. This is intuitive: the better the ideas that can emanate from innovation, the less important is worker mobility for transmitting ideas.

While we believe that our estimation strategy yields the most likely parameter estimates in light of our model, these results allow us to conjecture about the growth share when varying the parameters of the model. For instance, in our estimation of θ, the sample could over-represent firms with larger productivity and firm growth, which would yield an

upward-biased estimate of θ. Hence, the true mobility share might lay somewhat lower than our estimate. Given the range of estimates suggested in Lucas and Moll (2014), our model would however still predict a growth share of at least about 50%.

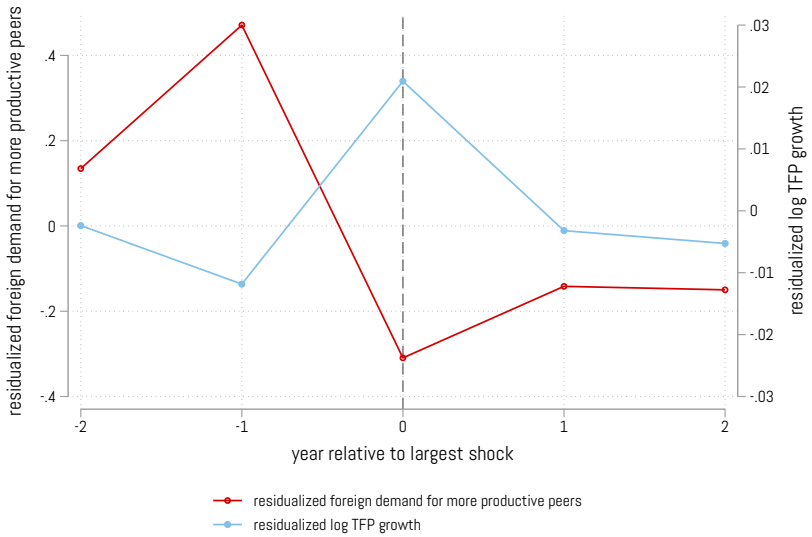
A.3 Data Overview

Data Set	Period	Variables
Worker data – Swedish Longitudinal Integrated Database for Health Insurance and Labour Market Studies (LISA, Longitudinell Integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier)	1990-2019	worker id, firm id, age, year of graduation, gender, income, year, occupation, education
Firm data (Företagens Ekonomi)	1997-2019	firm id, firm size, value added, output, capital, year, industry
Customs data (Utrikeshandel med varor)	1997-2019	firm id, export/import flow, value, quantity, year, country
Product data (Industrins Varuproduktion)	1997-2019	firm id, year, product code, value of production, quantity
Death data (National Board of Health and Welfare)	1997-2016	worker id, year, cause of death
R&D data (Research and Development survey in private sector)	1997-2019	firm id, year, R&D expenditure

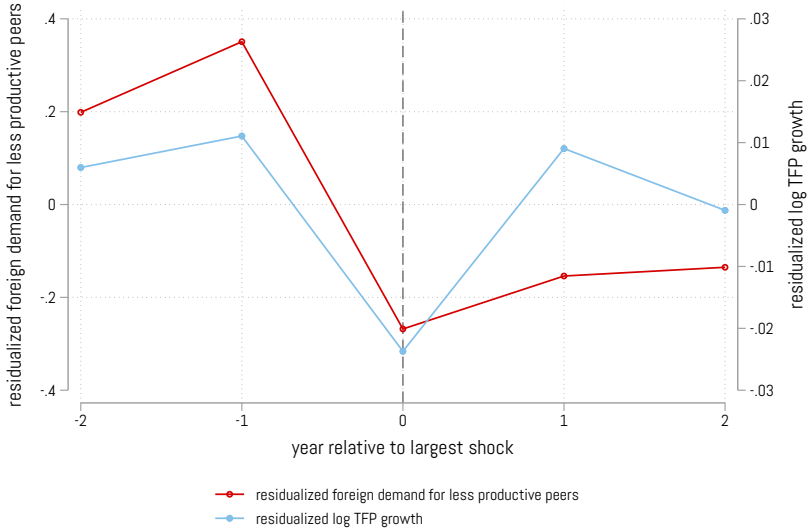
Table A.1: Variables across datasets.

A.4 Additional Empirical Evidence

A.4.1 Trade shocks using TFP growth



(a) Effect on productivity of shocks to peers with above-median productivity.

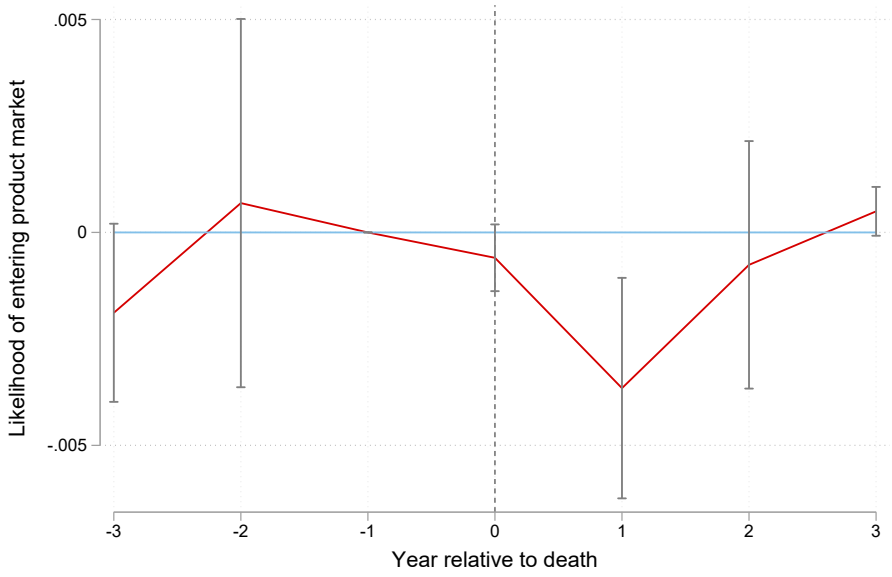


(b) Effect on productivity of shocks to peers with below-median productivity.

Figure A.2: Causal effect of hiring on firm performance.

Notes: See Figure 3. Moreover, total factor productivity (TFP) is estimated using two-digit sector-specific production functions estimated according to Levinsohn and Petrin (2003). The mean residuals across firms for each year relative to the event are plotted in the figure. We separate peers into firms above and below median productivity. Panel a shows events based on shocks to peers with above-median productivity, and panel b to firms with below-median productivity.

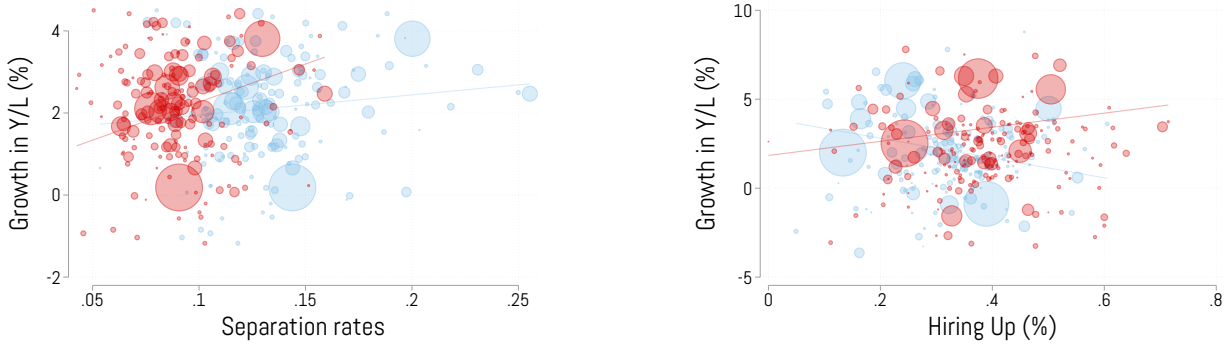
Figure A.3: Event study of death on product expansion.



Notes: The figure shows the impact of a worker death on whether a firm starts producing a certain product when the worker that died had experience in producing exactly that product. The corresponding regression specification is $X_{ijt} - X_{ij,t-1} = \sum_{\tau=t-3}^{t+3} \alpha_\tau \times I_{\text{period}_\tau} \times \text{years}_{ij} + \gamma_{ij} + \eta_t + \varepsilon_{it}$ where X_{ijt} takes the value 1 if firm i produces product j in year t and years_{ij} indicates the number of years of experience the dying worker had of producing product j. We also control for contemporaneous firm sales. In this figure we include only events in which the firms do not replace the disappearing workers.

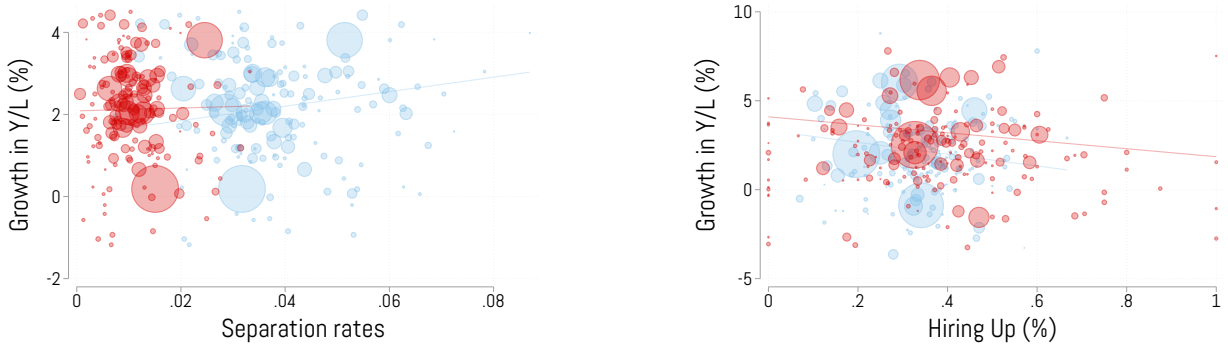
A.4.2 Regressions Motivation

Figure A.4: Productivity growth and mobility (only EE mobility).



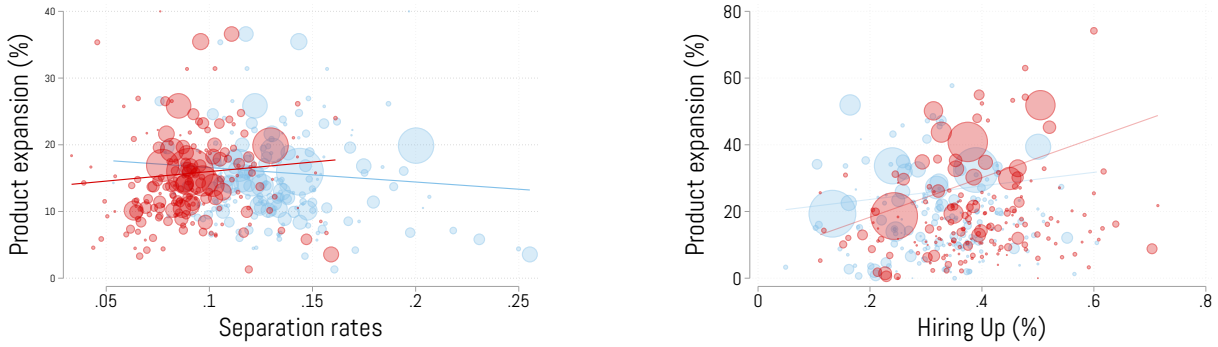
Notes: The left column shows binned scatter plots of the separation rate and the growth in labor productivity for occupations with below median wages (blue) and top decile occupations (red).The right hand side shows the share of workers who last worked at higher-productivity firms before entering the current firm and the growth in labor productivity for these two types of workers. Ranking of firms is established in the year prior to mobility based on observed Y/L. A unit of observation is a 4-digit industry. Data for Sweden, 1997–2019.

Figure A.5: Productivity growth and mobility (only EU or UE mobility).



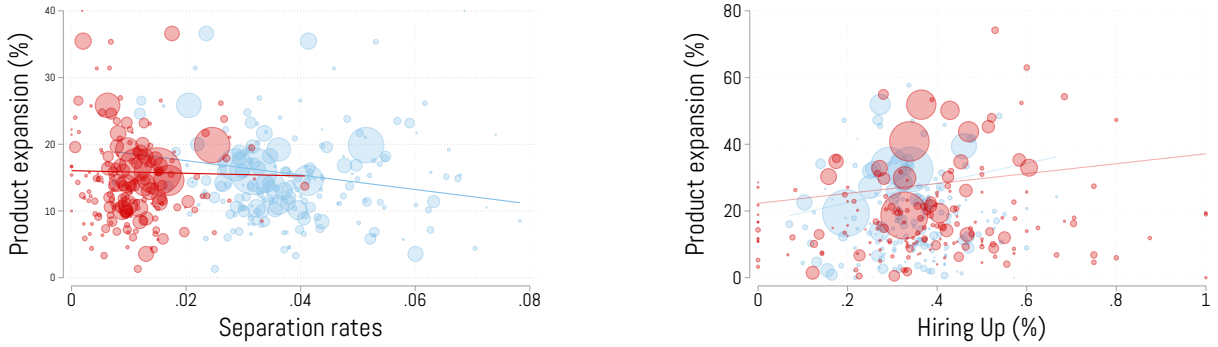
Notes: The left column shows binned scatter plots of the separation rate and the growth in labor productivity for occupations with below median wages (blue) and top decile occupations (red).The right hand side shows the share of workers who last worked at higher-productivity firms before entering the current firm and the growth in labor productivity for these two types of workers. Ranking of firms is established in the year prior to mobility based on observed Y/L. A unit of observation is a 4-digit industry. Data for Sweden, 1997–2019.

Figure A.6: Product expansion and mobility (only EE mobility).



Notes: The left panel shows binned scatter plots of the separation rate and the likelihood of product expansion for all workers (blue) and top decile occupations as categorized by average earnings (red). The right hand side shows the share of workers who last worked at higher-productivity firms before entering the current firm and the likelihood of product expansion for these two types of workers. Ranking of firms is established in the year prior to mobility based on observed Y/L. A unit of observation is a 4-digit industry and products are denoted at 8-digit. Data for Sweden, 1997–2019.

Figure A.7: Product expansion and mobility (only EU or UE mobility).



Notes: The left panel shows binned scatter plots of the separation rate and the likelihood of product expansion for all workers (blue) and top decile occupations as categorized by average earnings (red). The right hand side shows the share of workers who last worked at higher-productivity firms before entering the current firm and the likelihood of product expansion for these two types of workers. Ranking of firms is established in the year prior to mobility based on observed Y/L. A unit of observation is a 4-digit industry and products are denoted at 8-digit. Data for Sweden, 1997–2019.

Table A.2: Regression Results - Labor Productivity

Dep. var.:	Growth in labor productivity					
Controls:	No controls		Y/L		Y/L + volatility	
	Bottom half	Top dec.	Bottom half	Top dec.	Bottom half	Top dec.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Separation rate	0.04*	0.11***	0.10***	0.15***	0.05**	0.06
	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)
Observations	171	171	171	171	170	170
Mean growth	0.02	0.02	0.02	0.02	0.02	0.02
Mean sep. rate	0.16	0.09	0.16	0.09	0.16	0.09
Panel B						
Hiring up	-0.06***	0.03**	-0.00	0.05***	0.03**	0.06***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	182	178	182	178	182	178
Mean growth	0.02	0.02	0.02	0.02	0.02	0.02
Mean hiring up	0.33	0.38	0.33	0.38	0.33	0.38
Controls						
Labor productivity			✓	✓	✓	✓
Sector sales volatility					✓	✓
Sector foreign demand volatility					✓	✓

Notes: The table shows regression estimates together with standard errors for the regression specification $\Delta P_{st} = \alpha_0 + \mathrm{Y}_{st}\beta + X\Gamma_t + \epsilon_{st}$ where Y is either the separation rate or the share of hires from higher productivity firms. The unit of observation is a sector. The control vector X contains labor productivity, sales or foreign demand volatility, computed as sector average of firm-specific values.

Table A.3: Regression Results - Product Expansion

Dep. var.:	Product expansion					
Controls:	No controls		Y/L		Y/L + volatility	
	Bottom half	Top dec.	Bottom half	Top dec.	Bottom half	Top dec.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Separation rate	-0.23**	0.15	-0.09	0.30*	-0.46***	-0.12
	(0.10)	(0.17)	(0.11)	(0.16)	(0.12)	(0.20)
Observations	171	171	171	171	170	170
Mean product expansion	0.14	0.14	0.14	0.14	0.14	0.14
Mean sep. rate	0.16	0.09	0.16	0.09	0.16	0.094
Panel B						
Hiring up	0.22***	0.59***	0.25***	0.64***	0.243***	0.66***
	(0.08)	(0.10)	(0.08)	(0.10)	(0.09)	(0.101)
Observations	180	177	180	177	180	177
Mean product expansion	0.17	0.18	0.18	0.18	0.18	0.18
Mean hiring up	0.33	0.38	0.33	0.38	0.33	0.38
Controls						
Labor productivity			✓	✓	✓	✓
Sector sales volatility					✓	✓
Sector foreign demand volatility					✓	✓

Notes: The table shows regression estimates together with standard errors for the regression specification Product Exp. $= \alpha_0 + \mathrm{Y}_{st}\beta + X\Gamma_t + \epsilon_{st}$ where Y is either the separation rate or the share of hires from higher productivity firms. The unit of observation is a sector. The control vector X contains labor productivity, sales or foreign demand volatility, computed as sector average of firm-specific values.

Table A.4: Regression Results - Labor Productivity with Standardized Regressors and R&D

Dep. var.:	Growth in labor productivity					
Controls:	No controls		Y/L		Y/L + volatility	
	Bottom half	Top dec.	Bottom half	Top dec.	Bottom half	Top dec.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Separation rate	0.002**	0.003***	0.004***	0.004***	0.001	0.002*
(standardized)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D activity	0.001	0.001	-0.002***	-0.003***	-0.002***	-0.003***
(standardized)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	171	171	171	171	170	170
Mean growth	0.02	0.02	0.02	0.02	0.02	0.02
Mean sep. rate	0.162	0.09	0.16	0.09	0.16	0.09
Panel B						
Hiring up	-0.005***	0.006***	-0.001	0.006***	0.003*	0.008***
(standardized)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R&D activity	0.000	0.008***	-0.002	0.004***	0.001	0.005***
(standardized)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	182	178	182	178	182	178
Mean growth	0.02	0.02	0.02	0.02	0.02	0.02
Mean hiring up	0.33	0.38	0.33	0.38	0.33	0.38
Controls						
Labor productivity			✓	✓	✓	✓
Sector sales volatility					✓	✓
Sector foreign demand volatility					✓	✓

Notes: The table shows regression estimates together with standard errors for the regression specification $\Delta P_{st} = \alpha_0 + \mathrm{Y}_{st}\beta + X\Gamma_t + \epsilon_{st}$ where Y is either the standardized separation rate or the standardized share of hires from higher productivity firms. We also include the standardized R&D. The unit of observation is a sector. The control vector X contains labor productivity, sales or foreign demand volatility, computed as sector average of firm-specific values.

Table A.5: Regression Results - Product Expansion with Standardized Regressors and R&D

Dep. var.:	Product expansion					
Controls:	No controls		Y/L		Y/L + volatility	
	Bottom half	Top dec.	Bottom half	Top dec.	Bottom half	Top dec.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Separation rate	-0.000	0.007*	-0.000	0.007*	-0.014***	-0.004
(standardized)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
R&D activity	0.016***	0.017***	0.017***	0.017***	0.015***	0.017***
(standardized)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	171	171	171	171	170	170
Mean product expansion	0.14	0.14	0.14	0.14	0.14	0.14
Mean sep. rate	0.16	0.09	0.16	0.09	0.16	0.094
Panel B						
Hiring up	0.044***	0.083***	0.045***	0.083***	0.051***	0.088***
(standardized)	(0.008)	(0.010)	(0.008)	(0.010)	(0.009)	(0.010)
R&D activity	0.043***	0.070***	0.043***	0.065***	0.048***	0.066***
(standardized)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	180	177	180	177	180	177
Mean product expansion	0.17	0.18	0.18	0.18	0.18	0.18
Mean hiring up	0.33	0.38	0.33	0.38	0.33	0.38
Controls						
Labor productivity			✓	✓	✓	✓
Sector sales volatility					✓	✓
Sector foreign demand volatility					✓	✓

Notes: The table shows regression estimates together with standard errors for the regression specification Product Exp. $= \alpha_0 + \mathrm{Y}_{st}\beta + X\Gamma_t + \epsilon_{st}$ where Y is either the standardized separation rate or the standardized share of hires from higher productivity firms. We also include the standardized R&D. The unit of observation is a sector. The control vector X contains labor productivity, sales or foreign demand volatility, computed as sector average of firm-specific values.

Table A.6: Regression Results - Product entry and experience of workers that die.

Dep. var: Probability of entering a product market		
	Low-skilled (1)	High-skilled (2)
Dep. var.: Dummy indicating whether firm i starts to produce product j in year t		
Panel A: Years of experience		
Years of experience of producing product j	-0.0007***	-0.0013***
of workers that die in firm i in year $t-1$	(0.0001)	(0.0003)
N	56,903,732	54,487,288
Panel B: Workers with experience		
The number of workers with experience	-0.0066***	-0.0211***
of producing product j that die in firm i in year $t-1$	(0.0006)	(0.0023)
N	56,903,732	54,487,288
Year FE	√	√
Product-firm FE	√	√
Employment (log)	√	√

Notes: The table shows regression estimates together with standard errors for the regression specification Product Exp.$_{sjt} = \alpha_0 + \mathrm{Y}_{sj,t-1}\beta + X\Gamma_t + \epsilon_{st}$ where Y is either the years of experience from working in firms that produce product j of workers with unexpected deaths (panel A), or the number of workers with such experience that die unexpectedly (panel B). The unit of observation is firm-product-year. The control vector X contains log employment at the firm level. The dependent variable is a dummy for whether the firm starts producing product j in year t. The left column contains only deaths of workers with an education below university. The right column contains only deaths of workers with an education at at least university level. Standard errors clustered at the firm-product level are reported in brackets. *** denote a p-value below 1 percent, ** below 5 percent, and * below 10 percent.

Table A.7: Regression Results - Product entry and experience of workers that die.

Dep. var: Log sales of product j		
	Low-skilled (1)	High-skilled (2)
Dep. var.: Log sales of product j in year t		
Panel A: Years of experience		
Years of experience of producing product j	-0.02***	-0.04***
of workers that die in firm i in year $t-1$	(0.002)	(0.006)
N	56,903,732	54,487,288
Panel B: Workers with experience		
The number of workers with experience	-0.09***	-0.36***
of producing product j that die in firm i in year $t-1$	(0.011)	(0.049)
N	56,903,732	54,487,288
Year FE	√	√
Product-firm FE	√	√
Employment (log)	√	√

Notes: The table shows regression estimates together with standard errors for the regression specification Log sales$_{sjt} = \alpha_0 + \mathrm{Y}_{sj,t-1}\beta + X\Gamma_t + \epsilon_{st}$ where Y is either the years of experience from working in firms that produce product j of workers with unexpected deaths (panel A), or the number of workers with such experience that die unexpectedly (panel B). The unit of observation is firm-product-year. The control vector X contains log employment at the firm level. The left column contains only deaths of workers with an education below university. The dependent variable is the log production value of firm s of product j in year t. The right column contains only deaths of workers with an education at at least university level. Standard errors clustered at the firm-product level are reported in brackets. *** denote a p-value below 1 percent, ** below 5 percent, and * below 10 percent.

A.5 Estimation Result

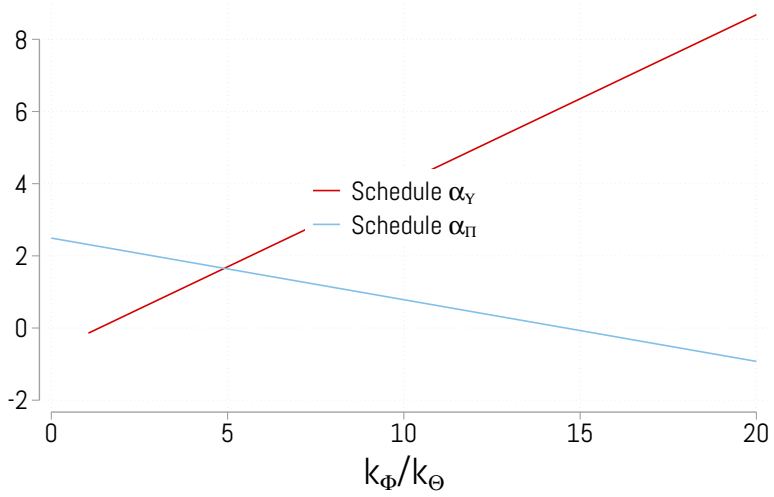
A.5.1 Parameter Estimates

Table A.8: Estimated parameters

	Description	Value
	Innovation Parameters	
θ	PL exponent	0.76
α	Y/L- Disruption	0.97
β	Y/L- Innovation	0.02
γ	Growth Rate	0.03
	Labor Market Parameters	
$\bar{N}^I(1-u)/\bar{N}^J$	Average Firm Size	50.91
u	Unemployment Rate	0.07
UE	Job Arrival UE	0.01
EE	Job Arrival EE	0.03
δ	Job Displacement	0.02
Observations		242 380

Notes: The table shows parameter estimates.

Figure A.8: Innovation Intensities



Notes: The figure shows a graphical representation of the two equations pinning down the estimated α_Υ, α_Π for a given $\frac{k_\Phi}{k_\Theta}$ and the set of the remaining parameter estimates. The two equations are

$$\alpha_\Upsilon = \frac{\left(\frac{\gamma}{\theta} - UE\frac{k_\Phi}{k_\Theta} - EE - \delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right) - (UE-\delta)\frac{(1-u)}{f}\right)}{\beta\frac{k_\Phi}{k_\Theta}}$$

$$\alpha_\Pi = \frac{\delta\frac{k_\Theta u}{k_\Phi} - \frac{\gamma u^2 f}{\theta(1-u)} - UE}{(UE-\delta)}$$

A.5.2 Mobility patterns over time

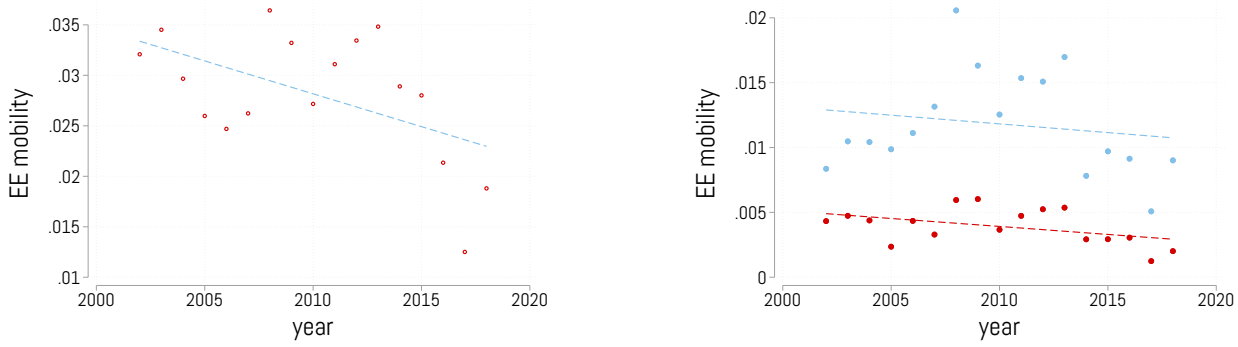


Figure A.9: Hiring Rates Evolution

Notes: The left panel shows the average over time of the estimated rate of firm hires from other firms over all population groups. The right figure subdivides the sample into those in the top and bottom income groups.

Table A.9: Sub-sample Analysis

	Description	All	Before	After
	Innovation Parameters			
θ	PL exponent	0.76	0.67	0.94
α	Y/L- Disruption	0.97	0.91	0.90
β	Y/L- Innovation	0.020	0.019	0.023
γ	Growth Rate	0.028	0.025	0.038
	Labor Market Parameters			
$\bar{N}^I(1-u)/\bar{N}^J$	Average Firm Size	50.91	52.55	48.69
u	Unemployment Rate	0.072	0.068	0.076
UE	Job Arrival UE	0.013	0.015	0.010
EE	Job Arrival EE	0.027	0.028	0.027
δ	Job Displacement	0.022	0.020	0.026
Observations		233 287	133 948	99 339

Notes: The table shows parameter estimates for the whole sample and two sub-sample analysis, once for the period before 2009 and once after 2009.

Appendix B Cross-Country Evidence Mobility Rates and Growth

Using the cross-country data from Donovan et al. (2023), we examine the cross-country correlation of the worker mobility rate, understood as the share of the population that arrives at a new job (EE mobility) or from unemployment (UE) and the average growth rate of output per capita over the sample period. Figure B.1 shows a positive correlation, mostly driven by low-income countries. While the sample is small, we find a significant correlation in table B.1.

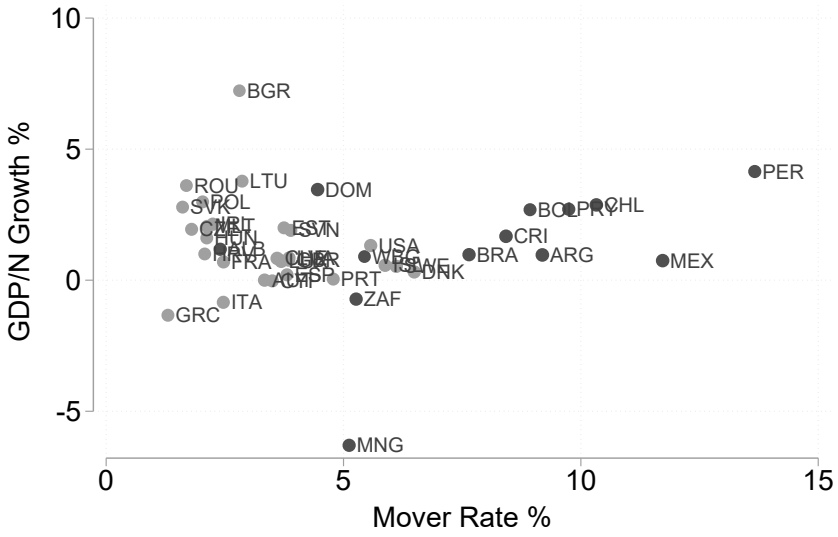


Figure B.1: Cross-Country Evidence

Notes: The figure shows the correlation of the mover rate, defined as the rate of new worker arrival from employment (EE) or unemployment (UE) and the average output per worker growth. High income countries are plotted in dark shade.

Table B.1: Cross-country Analysis

	(1)	(2)	(3)	(4)
Mover Rate %	0.251**	0.241**	0.372***	0.374***
	(0.085)	(0.086)	(0.108)	(0.111)
High Inc.=1 × Mover Rate %			-0.293*	-0.298*
			(0.159)	(0.158)
Observations	456	456	456	456
Weight		W		W
Interact.			Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Notes: The table shows parameter estimates for the regression of average growth in output per worker on the mover rate, defined as the rate of new worker arrival from employment (EE) or unemployment (UE). As controls we add the level of output per capita and the classification into rich and non-rich countries, following Donovan et al. (2023). Weighting is performed in columns (2) and (4) using log output per capita. In column (3) and (4), the mover rate is interacted with the classification for rich countries.