Application to the NBER Summer Institute 2025

Applicant Information

- **Name:** Kerstin Holzheu
- **Email:** kerstin.holzheu@sciencespo.fr
- **Affiliation:** Sciences Po (CNRS)
- **PhD Date:** May 2018, University of Chicago
- **Website:** www.kerstinholzheu.com

Research Summary My research focuses on worker mobility as a key mechanism shaping wage dynamics, productivity, and labor market structure. Across several papers, I study how mobility reflects and drives economic outcomes at both microeconomic and macroeconomic levels, using matched-employer employee data, survey data and matches of survey and administrative data for various countries.

In *The Role of Workers in Knowledge Diffusion Across Firms* (with Anders Akerman), I show that mobility is a major contributor to aggregate productivity growth. In *How Much Should We Trust Estimates of Firm Effects and Worker Sorting?* (with Stéphane Bonhomme, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler), I demonstrate how limited worker mobility biases common estimates of firm and worker wage effects. Worker mobility also serves as an empirical tool for identifying wage-setting institutions. In *Wage Bargaining and Wage Posting Firms* (with Jean-Marc Robin), I use observed worker transitions (among other moments) to distinguish between firms that post wages and those that negotiate, showing that wage-bargaining firms exhibit higher productivity but also more inefficient mobility.

Worker mobility also helps explain life-cycle wage growth differences across countries. In *Life-Cycle Wage Growth and Firm Productivity in Developed and Developing Economies* (with Juan Munoz), I show that mobility—mediated by differences in the firm productivity distributions—accounts for steep wage growth in richer economies. In *The Two Faces of Worker Specialization* (with Zsófia Barany), I use mobility patterns to identify both the benefits and risks of specialized skill sets. In *Gender Differences in Amenities, Wages, and Firms* (with Yana Gallen, Nabanita Datta Gupta, and Kristian Stamp Hedeager), I find that gendered preferences for job amenities, especially around motherhood, drive mobility across firms and explain a sizable share of the gender compensation gap once amenities are valued. Finally, in *Inheritance Taxes and Family Firms in Germany* (with Charlotte Bartels, Theresa Buehrle, Gedeão Locks, and Duncan Roth), I show that tax incentives can prompt firms to shed workers prior to ownership transfer, resulting in involuntary separations. Collectively, my work highlights how mobility is both a reflection of economic forces and a driver of key labor market outcomes.

Distinctive Perspective I Bring My research bridges micro-level labor market frictions and macroeconomic outcomes through the lens of worker mobility. Combining structural modeling with detailed administrative data across multiple countries, I aim to understand how in-

dividual choices and firm behaviors aggregate to shape inequality, productivity, and growth. I believe this cross-national, micro-to-macro perspective will contribute empirical depth and comparative insights to the Summer Institute's community.

What I Hope to Gain I look forward to engaging with leading researchers working at the intersection of labor economics and macroeconomics. Participating in the Summer Institute would allow me to gather feedback on ongoing projects, explore collaborations, and better align my empirical work with recent advances in labor economics research.

Sessions of Interest I am particularly interested in the following sessions:

- **SI 2025 The Micro and Macro Perspectives of the Aggregate Labor Market**
  July 14-17, 2025
  Organizer(s): Philipp Kircher, Guido Menzio, and Giuseppe Moscarini
- **SI 2025 Micro Data and Macro Models**
  July 14-17, 2025
  Organizer(s): Erik Hurst, Greg Kaplan, and Giovanni L. Violante
- **SI 2025 Economic Growth**
  July 10-11, 2025
  Organizer(s): Ufuk Akcigit, Francisco J. Buera, and David Lagakos
- **SI 2025 Macroeconomics and Productivity**
  July 15, 2025
  Organizer(s): Susanto Basu, Nicholas Bloom, Raffaella Sadun, and Chad Syverson
- **SI 2025 Labor Studies**
  July 21-23, 2025
  Organizer(s): David Arnold, David Autor, Zoe B. Cullen, Alessandra Fenizia, Matthew S. Johnson, Kurt J. Lavetti, Alexandre Mas, Pascual Restrepo, and Nina Roussille
- **SI 2025 Gender in the Economy**
  July 22-23, 2025
  Organizer(s): Marcella Alsan, Jessica Goldberg, Claudia Goldin, Claudia Olivetti, and Melanie Wasserman

Kerstin Holzheu

kerstin.holzheu@gmail.com http://www.kerstinholzheu.com

Office Contact Information

Sciences Po (Paris)
28 Rue des Saints-Pères
75007 Paris, France
+33 7 66 44 10 05

Appointments

Visiting Fellow/ Visiting Professor Yale University	2023/2024
Visiting Fellow EIEF	3/2023
Sciences Po, Assistant Professor	since 2019
Institute for Fiscal Studies, PostDoc	2018-2019

Other Affiliation

IZA Fellow	since 2018

Education

Ph.D. Economics, The University of Chicago	2018
MSc Macroeconomic Policy and Financial Markets, Barcelona GSE	2010
MA & BA Empirical Social Sciences and MA Applied Economics	2004-2009
French-German Double Diploma in Social Sciences	
University of Stuttgart, Germany & Sciences Po Bordeaux, France	

Research Projects

How much Should we Trust Estimates of Firm Effects and Worker Sorting?, joint with Stephane Bonhomme, Thibaut Lamadon, Elena Manresa, Magne Mostad, Bradley Setzler (JOLE 2023)

The Role of Workers in Knowledge Diffusion Across Firms, joint with Anders Akerman

Wage Bargaining and Wage Posting Firms, joint with Jean-Marc Robin

The Two Faces of Worker Specialization, joint with Zsofia Barany

Life-Cycle Wage Growth and Firm Productivity in Developed and Developing Economie, joint with Juan Munoz

Gender Differences in Amenities, Wages, and Firms, joint with Nabanita Datta Gupta, Yana Gallen and Kristian Stamp Hedeager

Separations on the Job Ladder, joint with Lewin Nolden

Worker Specialization and the Aggregate Economy, joint with Zsofia Barany

Inheritance taxes and family firms in Germany, joint with Charlotte Bartels, Theresa Buehrle, Gedeão Locks and Duncan Roth

Bicycle Paths and Wages, joint with Elena Mattana

Acqui-Hires, joint with Jingnan Liu

Conferences and Presentations

2025	CREST, (prospective) SED, World Congress Econometric Society Joint Columbia/Sciences Po Workshop, INSEAD/College de France/PSE, EEA IAB Workshop "Identifying Worker and Firm Quality" 3rd Oslo Public-Labor Workshop
2024	AEA, Yale University, IE University, Lisbon Macro Conference, SED, GEA Conference, ECB, Macro-Labor Workshop Konstanz, IFS
2023	SOLE,University of Mannheim, University of Bristol, EIEF, Bocconi, GEA Conference
2022	SOLE, SED, University of Edinburgh, University of Stavanger, NBER Wage Dynamics in the 21st century, Essex SaM, Christmas Conference Berlin
2021	SOLE, Spring Meeting of Young Economists, Labor Market Workshop University Bonn & Mannheim, EEA, IESEG, Sciences Po
2020	Banque de France, Sciences Po
2019	University of Melbourne, UNSW, Royal Holloway (University of London) E1-Macro QMQM Workshop (Queen Mary University)
2018	Aarhus University, Bonn University, CEMFI, ECB, EINAUDI, IESE, IFS USC Marshall, University of Montreal, PennState University SciencesPo, UBC, UCSB
2016	Midwest Search and Matching Workshop
2015	Federal Reserve Bank of New York

Honors, Scholarships, Fellowships and Grants and Prizes

ANR 2024 (EUR 50 000), SAB Sciences Po (EUR 40 000), Banque de France/Sciences Po Partnership Research Grant (EUR 27 000 - 2020-2025), University of Chicago Data Award (USD 5 000), Social Sciences Full Fellowship University of Chicago 2011-17, CSWEP Fellowship Federal Reserve Bank of New York 2015, Tuition Waver Barcelona Graduate School of Economics 2010, Tuition Refund due to Exceptional Performance (University of Stuttgart, 2010/2012)

Teaching Experience

Sciences Po
Core Economics (2019-2025), Reading Group Macro+, Reading Group Labor and Public Economics, Labor Economics and Policy

University of Chicago
Department of Economics: (Lecturer) Fiscal and Monetary Policy (Autumn 2014 & Spring 2015), (TA) Introduction to Advanced Macroeconomic Analysis (Winter 2013), Introduction to Microeconomics & Introduction to Macroeconomics (Winter 2016-Autumn 2017), Advanced Macroeconomics, Honors (Autumn 2012)

Booth School of Business : (TA) Leading and Managing Teams (Spring 2017), Going To Market: Managing Channel Strategy (Spring 2016)

Service to the profession

Refereeing	American Economic Review, Journal of Political Economy, Review of Economic Studies, Journal of Political Economy - Micro, Economic Journal, Banque de France, Economic Policy

The Role of Workers in Knowledge Diffusion Across Firms*

Anders Akerman and Kerstin Holzheu‡

April 22, 2025

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 60% 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

*We thank seminar participants and discussants at IE University, IFS, NOITS, Lisbon Macro Workshop, SED 2024, Yale University, as well as Johannes Boehm, Pierre Cahuc, Nicolas Coeurdacier, Ilse Lindenlaub, Isabelle Mejean, Giuseppe Moscarini, Michael Peters, Martin Souchier and Fabrizio Zilibotti for helpful discussions. We thank Statistics Sweden for data access. Akerman gratefully acknowledges support from the Research Council of Norway (grant no. 326000). Holzheu thanks the Banque de France for financial support.

‡Akerman: University of Stavanger (anders.akerman@gmail.com), Holzheu: Sciences Po (CNRS) & IZA (kerstin.holzheu@sciencespo.fr)

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 three main contributions. First, we develop a novel multi-worker-firm environment with on-the-job search, building on Bilal et al. (2022), that enables us to disentangle the contributions to economic growth arising from labor mobility and firm-generated innovation. 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. 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 as compared to the first contributions on productivity diffusion (Lucas and Moll, 2014). 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. As a second contribution, 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 vertical productivity changes, such as increases in output per worker, as well as horizontal 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. Finally, we estimate the aggregate implications of worker mobility, drawing on comprehensive data from the Swedish manufacturing sector, where innovation has a more pronounced influence compared to other economic sectors. Our findings highlight the

amplifying role of worker mobility in fostering economic growth. Quantitatively, we estimate that worker mobility accounts for over 60% of aggregate growth in the manufacturing sector. This reflects the fact that, since only a small fraction of firms engage in R&D (Klette and Kortum, 2004), the diffusion of knowledge through mobile workers—reaching a broader set of firms—must play a correspondingly larger role in driving sector-wide productivity gains. Our estimates reveal that a drop in worker mobility (for example due to employment protection legislation) of 1 percentage points would lead to a fall in aggregate growth of 0.69 percentage points. In a split-sample analysis spanning the past two decades, we find a modest decline in the contribution of worker mobility to knowledge diffusion, coinciding with reduced mobility rates and increased R&D intensity. Our results indicate that this decline has been partly offset by a rise in knowledge adoption, suggesting that human resource management practices may play a mitigating role in addressing potential productivity concerns stemming from reduced worker mobility.

In our theoretical framework, we conceptualize workers as vessels of knowledge. In our framework, knowledge raises output per worker, reflecting the presence of transferable, general human capital.[1] Firms generate new ideas through R&D and transmit these ideas to their workers, thereby assuming a dual role as both innovators and knowledge disseminators. Worker mobility, then, acts as an amplification mechanism of R&D efforts in the economy. Unlike most labor-search frameworks with multi-worker firms, where workers merely coexist in production (e.g., Gulyas, 2024; Grübener and Rozsypal, 2024; Moscarini and Postel-Vinay, 2013), our model allows the mobility of one worker to affect the marginal productivity of others within the same firm, adding substantial complexity. As a result, the extent and direction of labor mobility emerge as central features of our framework. To the best of our knowledge, ours is the first theoretical framework to integrate knowledge spillovers in multi-worker firms with on-the-job search. This is particularly important given that, in many advanced economies, job-to-job flows account for the majority of hires and separations—often exceeding flows from unemployment by a factor of 2 to 3. This empirical pattern underscores the fact that most workers who change jobs do so without experiencing a spell of unemployment, making it essential for our framework to capture this empirical pattern. A key mechanism in our model is that, within our multi-worker-firm environment with constant returns, workers are willing to move not only to more productive firms but also to less productive ones. This occurs because their superior knowledge benefits firms with lower productivity more than their previous

[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).

employers. This mechanism enables firms to acquire knowledge from other firms through on-the-job search, bypassing the need to wait for highly knowledgeable workers to become unemployed. As a result, our model resolves a key trade-off present in frameworks that lack job-to-job mobility but allow for knowledge transfers. In such frameworks, unemployment is the primary channel for reallocating knowledge across the economy, creating an inherent tension between knowledge diffusion and worker inactivity. In contrast, our model eliminates this trade-off by facilitating continuous knowledge flow through worker mobility on the job. This mechanism also captures an important empirical feature of worker mobility—specifically, downward worker mobility from more to less productive firms (see, for instance, Sorkin, 2018), which is otherwise explained by compensating differentials (such as amenities or future wage growth cf. Holzheu and Robin, 2024).

We provide empirical evidence in support of our mechanism, using both suggestive aggregate evidence by comparing sectors of the economy and quasi-experimental evidence at the individual worker and firm level. Consistent with key predictions of our model, 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 using instances of both worker arrival as well as worker separations. 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. 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. Second, we build on a literature that exploits sudden and unexpected worker deaths to examine the effect of the loss of worker knowledge on firm product expansion. Specifically, we examine the causal effect of losing firm knowledge due to worker death on subsequent firm behavior, leveraging detailed information on workers' prior employment histories. We find that firms are significantly less likely to enter a given product market when the deceased worker had prior experience producing that specific product. 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.

Our model is set in a standard balanced growth setting. Despite the presence of multi-

worker firms, the model admits a tractable characterization in which the distribution of firm productivity evolves independently of the joint distribution of firm size and productivity. This separation greatly simplifies the analysis. To establish the existence of a balanced growth path, we adopt a guess-and-verify strategy, which in turn enables us to characterize on-the-job mobility—a central feature of empirical labor markets. The model yields closed-form expressions for aggregate growth, linking it explicitly to underlying structural parameters. Calibration is guided by empirical evidence on the productivity effects of worker arrivals and departures. A variance decomposition shows that our theoretical predictions regarding the contribution of worker mobility to growth are qualitatively consistent with observed data. Taken together, the results offer both theoretical and empirical support for the view that labor market frictions, by constraining worker reallocation, generate substantial growth losses.

This paper contributes to three main strands of the literature. The first examines how worker mobility affects firm outcomes, often by focusing on specific categories of employees—such as engineers (Harrigan et al., 2023), managers and CEOs (Bennedsen et al., 2020), national leaders (Jones and Olken, 2005), or inventors (Jaravel et al., 2018)—or by analyzing worker flows more broadly (Stoyanov and Zubanov, 2012). Other studies, such as Parsons and Vézina (2018), highlight the role of immigrants in shaping firms' export behavior. A related body of work has exploited exogenous worker exits—particularly due to death—as a source of identification (Bertheau et al., 2022; Jäger and Heining, 2019; Sauvagnat and Schivardi, 2023). While these prior studies have established that mobile workers can affect firm performance, we advance this literature by isolating the causal effect of the direction of worker mobility—that is, how the characteristics of the sending firm influence outcomes in the receiving firm. In contrast to Stoyanov and Zubanov (2012), who examine the impact of hiring from more productive firms, we leverage quasi-experimental variation arising from trade-induced shocks that generate exogenous changes in worker mobility. This identification strategy mitigates endogeneity concerns related to sorting or selection into specific hiring matches. Moreover, whereas existing work has used sudden deaths primarily to identify the effects of worker separations (e.g., Bertheau et al., 2022; Jäger and Heining, 2019; Sauvagnat and Schivardi, 2023), we introduce a novel use of unexpected worker deaths to study how attributes of prior employers affect the productivity trajectories of the firms that receive these workers. To the best of our knowledge, we are the first to examine whether a worker's prior experience in producing a specific product increases the likelihood that the receiving firm begins producing that same product. In doing so, we provide new, well-identified evidence on the role of individual workers in the transmission of product-specific knowledge across firms. Our findings highlight a previously underexplored mechanism by which labor mobility contributes

to the diffusion of firm capabilities and innovation.

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 and not only in a perturbation equilibrium.

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. First, we describe our theoretical framework and derive a balanced growth path of the economy in section 2. In section 3 we outline our data sources, section 4 shows suggestive correlations while section 5 provides quasi-experimental empirical

results on the importance of worker mobility for firm growth in Sweden. Motivated by the presented evidence, section 6 shows results for the decomposition of aggregate economic growth using our theoretical framework. Section 7 concludes.

2 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 2.1) and describe the value functions (cf. Section 2.2). 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 2.3) and the balanced growth path of the economy (cf. Section 2.4), using the previous insights and auxiliary assumptions. We first outline a model without on-the-job search in order to facilitate exposition. In Section 2.5, we relax this assumption and show how the main model equations change with on-the-job search. In Section 2.6 we extend the model further by introducing product choice and in Section 2.7 we introduce a propensity of knowledge adoption. All three extensions allow for a closer comparison of empirical data and model predictions in the next sections of the paper. Finally, in section 2.8, we summarize the models' predictions to allow their confrontation with the data. All derivations are relegated to Appendix Section A.2.

2.1 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 $G(P, t)$ with probability density function $g(P, t)$. Firms produce a single homogeneous good with output Y according to the constant

returns to scale technology $Y(P, N, t) = P_t N_t$.[2]

Workers can be employed or unemployed. There is a share u_t of unemployed workers, whose productivity follows the endogeneous productivity distribution $F(p, t)$, with probability density function $f(p, t)$. 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 $W(p, t)$ with probability density function $w(p, t)$. 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 $\max\{p_{it}, P_{jt}\}$.[3] While our model focuses on transferable productivity, the literature has attributed a non-negligible role to non-transferable productivity components, notably when discussing the effects of mass-layoffs.[4] 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

[2]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.

[3]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.

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

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 $V(P,t)$ with probability density function $v(P,t)$. 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 1 schematically represents these adaptation processes, using a discrete time scale for illustration purposes.

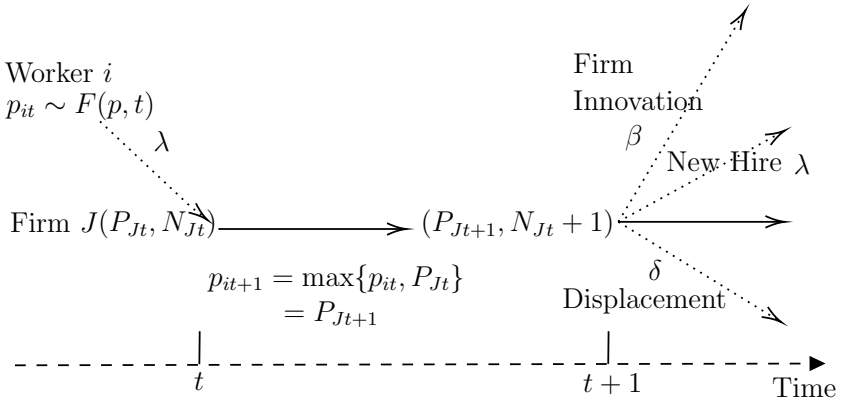


Figure 1: Mobility and Adaptation

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

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. (2021, 2022) 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 2.5.

2.2 Value functions 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

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

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

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

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.2.

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

$$rS(P, N, t) = (P - b(t))N + S_t + (\lambda - \delta) S_N + \omega(P, N, t) \tag{1}$$

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

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

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.2 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 2.4.

2.3 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 $\delta g(\tilde{P}/\alpha, t)$. 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 $\delta g(P, t)$. Hence, we can write the law of motions as

$$\begin{aligned}
&\frac{\partial g(P,t)}{\partial t} = \\
&\underbrace{\underbrace{f(P,t)G(P,t)\lambda}_{\text{Mobility Upgrade}} + \underbrace{\beta v(P,t)G(P,t)}_{\text{Innovation}} + \underbrace{\delta g\left(P/\alpha, t\right)}_{\text{Displacement}} + \underbrace{\mu g(P,t)}_{\text{New Firms}}}_{\text{Inflow}} \\
&\underbrace{- \underbrace{\lambda g(P,t)\bar{F}(P,t)}_{\text{Mobility Upgrade}} - \underbrace{\beta g(P,t)\bar{V}(P,t)}_{\text{Innovation}} - \underbrace{\delta g(P,t)}_{\text{Displacement}}}_{\text{Outflow}}
\end{aligned} \tag{2}$$

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 $\delta g(P,t)\frac{N_t^J}{u_t N_t^I}$ 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

$$\frac{\partial f(P,t)}{\partial t} = \underbrace{\underbrace{\delta g(P,t)\frac{N_t^J}{u_t N_t^I}}_{\text{Displacement}} + \underbrace{\mu w(P,t)\frac{N_t^I}{u_t N_t^I}}_{\text{New Entrants}}}_{\text{Inflow}} - \underbrace{\lambda f(P,t)\frac{N_t^J}{u_t N_t^I}}_{\text{Outflow: New Hires}} \tag{3}$$

2.4 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 1, iii) (f,g) satisfy the laws of motion in equations 3 and 2.*

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.2.4. 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.[5] 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.

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

$$\delta \frac{k_\Theta}{k_\Phi} = \lambda + \frac{\gamma}{\eta_p \theta} + \frac{\mu_w N^I}{N^J} \alpha_\Pi \tag{4}$$

$$\gamma = \theta \left(\lambda \frac{k_\Phi}{k_\Theta} + \beta \alpha_\Upsilon \frac{k_\Phi}{k_\Theta} + \mu_f + \delta \left(\alpha^{\frac{1-\theta}{\theta}} - 1 \right) \right) \tag{5}$$

where $\frac{N_t^J}{u_t N_t^I} = \eta_p$ (cf. Appendix Section A.2.5). Equation 5 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

[5] 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 $\frac{\partial g(P,t)}{\partial t} = -\gamma e^{-\gamma t}\Theta'(Pe^{-\gamma t}) - P\gamma(e^{-\gamma t})^2\Theta''(Pe^{-\gamma t})$

scalar α_Υ and the relative weights $\frac{k_\Phi}{k_\Theta}$). Equation 4 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. Importantly for our main mechanism, these equations reflect that higher worker mobility (λ) has the potential to increase economic growth (γ). We summarize this in result 2.

Result 2 (Labor Mobility and Growth) *Labor mobility increases growth in the economy.*

2.5 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.[6]

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,

[6]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 rationalizes such a distinction.

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

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

We hence know that the contract C is such that

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

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

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

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

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

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.[7]

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.[8] We verify that this surplus equation permits an affine representation (cf. Appendix Section A.2.7).

The productivity distribution of firms similarly changes to

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

[7] 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.

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

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

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

2.6 Extension with Product Choice

We previously entertained the assumption of the production of a single good. We now extend the model to allow for multiple products. This model extension allows us to interpret our model in light of the empirical data with multi-product firms and hence to bridge theoretical and empirical perspectives.

Additional Assumptions In this model extension, we build on Bernard et al. (2010) and define a set of products $\mathcal{I}$, where each product $i \in \mathcal{I}$ has a price p_i. The production of each product requires labor N_{ij} under a linear production technology. For a firm j with productivity A_j, the output of product i is given by:

$$y_{ij} = A_j N_{ij}. \tag{6}$$

Product choice occurs after all labor mobility has materialized, such that total firm size $\sum^{\mathcal{I}} N_{ij} = N_j$ is fixed at the time of product choice. Firms maximize total profits across products by choosing labor allocations across products N_{ij} taking as given prices of the goods p_i and its fixed costs of production F_i together with the total firm size N_j. Firms also take as given the average wage of the firm $\bar{w}_j$. As our analysis centers on worker mobility rather than wage determination, we abstract from the wage-setting mechanism, following Bilal et al. (2022). Importantly, our findings on product choice remain robust to different wage-setting protocols, provided that product selection depends on average wages rather than the precise distribution of workers within the firm. This assumption aligns with the notion that firms' production divisions operate with a degree of autonomy from their human resources departments.

Product Choice Firms maximize profits Π_j by determining production labor per product N_{ij} solving the problem

$$\Pi_j = \sum^{\mathcal{I}} \max_{N_{ij} \geq 0} \left(p_i A_j N_{ij} - \bar{w}_j N_{ij} - F_i \right), \quad \text{s.t.} \quad \sum^{\mathcal{I}} N_{ij} = N_j,$$

In Appendix section A.1, we show that higher firm productivity increases on average the number of products produced at the firm.

Result 3 (Product Choice) *The number of products chosen for production increases in firm productivity.*

As our model features a productivity cost of worker disappearance due to exogenous displacement, our model shows that a worker disappearance is associated with a decrease in the likelihood of product adoption.

Result 4 (Displacement Event & Product Choice) *A displacement event is accompanied by a lower likelihood of product expansion.*

2.7 Extension with Knowledge Adoption

We previously assumed that when a worker matches with a less productive firm, knowledge adoption by the less productive party occurs with certainty. We now relax this assumption by introducing heterogeneity in the likelihood of knowledge adoption. Specifically, adoption occurs at a match-specific rate v_i, drawn from a distribution $H(i)$ and revealed only after the hire. Firms form rational expectations about this process, with the average adoption rate given by $\omega = \int v_i, dH(i)$. Importantly, we assume that the distribution of v_i is independent of the worker's current productivity level P, consistent with standard treatments of match-specific productivity shocks.

To allow for such a scenario in our set-up given on-the-job search, we need to assume that ω is large enough such that mobility patterns are unchanged. Specifically, for this to be the case for all firms at all levels of productivity, we require the following assumption

Assumption 4 (Knowledge Adoption) *The average likelihood of knowledge adoption is high enough to ensure mobility of all workers to all firms.*

Using the mobility conditions, we find that this holds true for $\omega \geq 0.5$ [9]. We will test and verify this assumption later in the data. The equilibrium growth equations in our model then

[9] Using the affine surplus representation, we require for the case for a mobility from a high to low productive firm $P' < P$

$$\hat{S}(P,t) \leq \hat{S}(P',t) + \omega \left(\left(\hat{S}(P,t) - \hat{S}(P',t) \right) (N'+1) + \left(S^0(P) - S^0(P') \right) \right) I_{P-P' \geq 0}$$

This holds in all cases, for all $N' >= 1$, whenever $\omega \geq 0.5$.

change to

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

and the surplus equation changes to

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

2.8 Summary: Mobility and Growth Patterns

We now summarize the key mechanisms and predictions underlying our model. The model conceptualizes worker mobility as an amplification channel for R&D activities within the economy. Specifically, the model delivers four central predictions.

Prediction 1 *Higher worker mobility accelerates the diffusion of new knowledge.*

For a given firm productivity distribution $G(P)_t$, the probability that a firm improves its productivity through job-to-job mobility, $\omega\lambda s(1-u)\bar{G}(P)_t$ and through a hire from unemployment $\omega\lambda u\bar{G}(P)_t$, increases with λ. Greater labor mobility thus enhances the likelihood that firms adopt and implement new ideas, contributing to aggregate productivity growth. Thus, our model predicts that the extent of labor mobility influences productivity growth.

Prediction 2 *Increased hiring of workers from more productive firms facilitates knowledge transfer, allowing a larger share of firms to update their productivity levels.*

Given a job-to-job mobility rate of λ and an average adoption rate of ω, variation in the probability of encountering a worker from the upper tail of the productivity distribution, $\bar{G}(P)_t$, directly influences the pace of productivity growth. Thus, worker flows from highly productive firms serve as a conduit for disseminating best practices and technological advances across the economy. Hence, our model predicts that the direction of mobility affects productivity growth.

Prediction 3 *Variation in the knowledge adoption rate v_i by worker groups affects the likelihood of productivity growth.*

Given the rate of worker mobility and the ranking of the firm in the productivity distribution $G(P)_t$, a firm has a higher chance of productivity upgrade if matching with workers with high knowledge adoption rates v_i. Our model hence relates to the intuitive notion that not all workers are similarly impactful in knowledge transmission.

Prediction 4 *Exogenous worker displacements reduce productivity and hence the likelihood of product expansion.*

Given the drop in productivity due to a worker displacement at rate α, our model suggests that, on average, firms' number of products decrease after a worker disappearance.

In the following sections, we empirically evaluate these predictions using both sectoral data and detailed microeconomic evidence. A key implication of the model is that productivity gains manifest in two distinct ways: directly through increases in output per worker (Y/L) and indirectly through new product adoption, which reflects underlying productivity improvements. We refer to these two dimensions as vertical productivity growth and horizontal productivity growth, respectively. We will confront these outcome variables with the productivity shifters in our model: the extent and direction of mobility.

In the next sections, our empirical strategy is designed to trace the proposed mechanism within microeconomic data, focusing on sub-sectors of the economy and microeconomic data rather than the balanced growth path of the whole economy. After establishing empirical support for the mechanism, we then leverage the model's balanced growth path equation to analyze its implications for aggregate productivity dynamics and long-run economic growth.

3 Data

In the following, we outline our data sources in section 3.1 and discuss our sample in section 3.2.

3.1 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).[10] 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.[11] 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

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

[11]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).

Table 1: ICD diagnosis of Death – Sudden unexpected death

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

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 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.

3.2 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).[12].

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					

[12]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.

4 Suggestive Data Patterns

In the following, we consider the first three key Predictions 1 to 3 of our model (cf. section 2.8) across sectors of the economy. In this analysis, we consider that sectors can potentially vary in key characteristics of labor markets and firm productivity distributions, justifying a cross-sectoral perspective.

Specifically, we examine whether both the extent of worker mobility 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 to the correlation of productivity growth with R&D activity.

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 job-to-job mobility at the four-digit sector level as a measure for the extent of mobility. 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. We thereby aim at proxying for differences in the knowledge adoption rate v_i. 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. 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 2 showcases our results. In the left panel, we first see a scatter plot across sectors showing the level of labor productivity growth and the EE 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 assume that above median wage occupations feature higher knowledge adoption rates v_i. We see that there appears to be a positive correlation between worker

mobility and productivity growth among the workers with the highest level of knowledge adoption, 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 3, we analyze instead how worker mobility is 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 high wage occupations correlate positively with productivity growth (product expansion), while mobility by workers in the low wage 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 job-to-job mobility in general. Hiring from firms with higher levels of productivity appears to be associated with faster productivity growth, both for vertical (Figure 2) and horizontal (Figure 3) productivity growth. Both data patterns lead to statistically significant differences in correlation estimates across skill groups. In Online Appendix Tables A.2 and A.3 we perform regressions for the correlations depicted in the figures above.[13]

Importance of mobility One way to assess the importance of these correlations is to relate them to similar estimates on firms' effort on research and development (R&D). 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 2 (mean labor productivity growth) and 3 (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

[13]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 2: Vertical productivity growth: Growth in Y/L

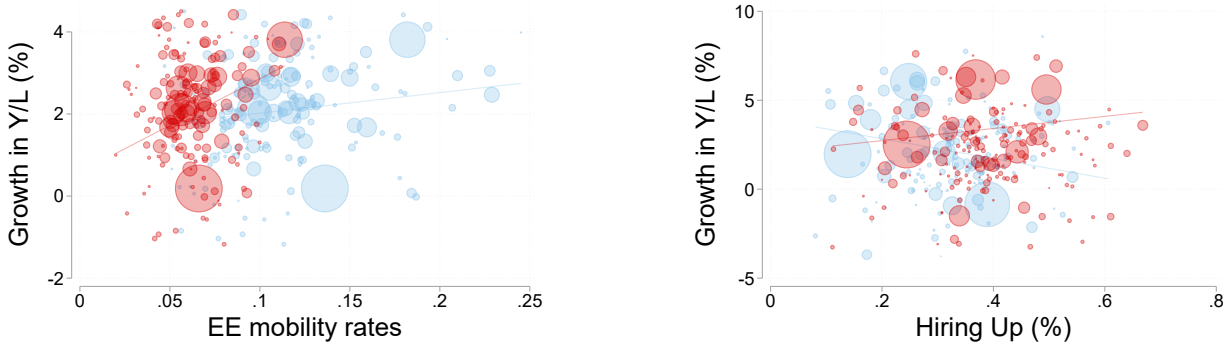
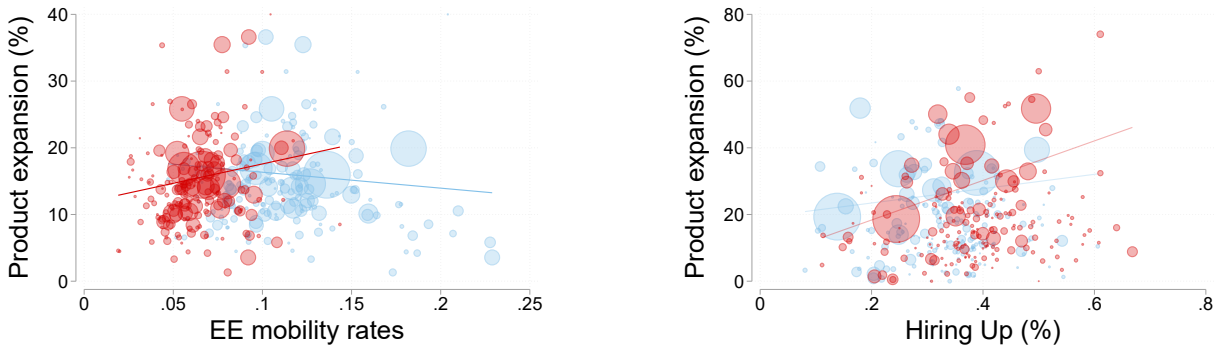


Figure 3: Horizontal productivity growth: Product expansion



Notes: Upper panel - The left column shows binned scatter plots of the job-to-job mobility 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 job-to-job mobility 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 the size of the circle is based on the total sales of the industry. Data for Sweden, 1997–2019.

from a more productive firm.

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				
EE mobility rate	0.003**	0.007***	-0.004	0.013*
(standardized)	(0.001)	(0.001)	(0.005)	(0.004)
R&D activity	0.003***	0.003***	0.016***	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.

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 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.[14]

[14]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

While these data patterns appear suggestive for key Predictions 1 to 3, we now leverage the full extent of the microdata to provide causal evidence on the suggested mechanisms.

5 Quasi-experimental evidence

We use individual-level data to examine the causal relationship between worker mobility and firm productivity, testing two core predictions of the model: that newly hired workers affect firm productivity (Prediction 2) and that worker departures influence product scope (Prediction 4). While the ideal—albeit impractical and unethical—empirical strategy would involve random assignment of workers and their knowledge across firms, we approximate this ideal using two sources of quasi-experimental variation.

Our first identification strategy leverages exogenous variation in hiring opportunities, generated by negative trade shocks to a firm's local peers—defined by industry and geography—following the shift-share approach of Hummels et al. (2014). Firms more exposed to foreign demand shocks through pre-sample export patterns face greater peer-level layoffs, creating quasi-random inflows of workers. We construct peer shocks by aggregating firm-level trade shocks and disaggregate them by source firm productivity to assess heterogeneity in knowledge transfer. Empirical results support the model's predictions. Negative shocks to productive peers raise hiring and lead to greater productivity gains, consistent with vertical knowledge flows. We focus on manufacturing firms, where export exposure dominates demand conditions, and control for worker fixed effects to address selection concerns.

Our second strategy tests whether worker knowledge shapes product scope. To isolate exogenous separations, we exploit sudden employee deaths. Using detailed employment histories, we proxy workers' knowledge by their product experience and track product line expansion post-separation. We find that firms are significantly less likely to expand into new product lines after a loss in worker human capital, consistent with horizontal productivity effects.

5.1 Local labor supply shocks

In this section, we examine whether newly hired workers contribute to subsequent productivity growth at the hiring firm. To identify this effect, we exploit plausibly exogenous variation in the origin of new hires induced by international trade shocks.

the two jobs.

Our approach builds on firm-level export data from the initial year of the sample. We calculate firm-specific demand shocks by interacting each firm's baseline export composition—disaggregated by product and destination country—with subsequent changes in global import demand. For example, if China reduces its imports of a particular type of steel bolt, then firms that exported this product to China in the base year are disproportionately exposed to the negative shock, relative to firms exporting the same product to other destinations or not exporting it at all. Similar shift-share methodologies have been employed in prior work, such as Hummels et al. (2014), who use firms' import patterns as shares and global export growth in origin countries as shifters to examine the effects of offshoring on domestic labor demand.

The variation in export exposure across firms is substantial. As shown in Table 4, the median product-destination cell is served by only two exporting firms, and the 90th percentile by just seven. Moreover, the median firm exports in only three product-destination cells and serves just two countries. This heterogeneity in export scope generates considerable firm-level variation in exposure to international demand shocks, enabling credible identification of their effects on hiring and productivity.

Specifically, we define the shock to firm j in year t as:

$$Z_{jt} = \sum_{c \in N_c} \sum_{p \in N_p} s_{jcp} M_{cpt}, \tag{7}$$

where N_c and N_p denote the sets of destination countries and HS-6 digit products, respectively, to which firms export. The term s_{jcp} represents the share of firm j's total exports in a pre-sample year (2003) accounted for by product p to country c, and M_{cpt} denotes total world import demand for product p by country c in year t. To prevent mechanical correlations between our instrument and domestic supply-side conditions, we exclude Swedish exports when constructing the import demand measure.

We then aggregate the shocks to local peer firms operating in the same sector and municipality, under the assumption that negative demand shocks to a firm's local peers lead to increased worker availability for that firm. Specifically, for each firm i, we define the peer shock as:

$$\tilde{Z}_{imkt} = \sum_{j \in J^{-i}_{m(i)k(i)t}} Z_{jt}, \tag{8}$$

Table 4: Export patterns.

	$50th$ Percentile	$90th$ Percentile	$99th$ Percentile	Observations
Country-product-year level				
Number of firms that export within each country-product-year cell	2	7	34	958,774
Firm-year level				
Number of destination country-products	3	43	252	11,645
Number of destination countries	2	18	54	11,645

Notes: Sample includes all firms included to compute shocks to local peers in this section. Firm trade data comes from Swedish Customs, and international trade data is from the UN Comtrade.

where $\tilde{Z}_{imkt}$ denotes the total shock to the set of peer firms located in municipality m, operating in sector k, and observed in year t, excluding firm i itself. The set $J^{-i}_{m(i)k(i)t}$ includes all firms in sector k and municipality m in year t, excluding firm i.

We implement an event-study-style analysis by identifying, for each firm, the year in which its local peers—defined as firms operating in the same municipality and sector—experienced their most severe negative shock to global import demand. This is the year in which $\tilde{Z}_{imkt}$ falls the most, and we refer to it as the event year, which is firm-specific. Using the year with the largest change in trade exposure as the event year enables us to examine the effects of salient and idiosyncratic shifts in global demand. This approach also permits the construction of an event-study framework even when events are not discrete or binary in nature. For example, Bhuller et al. (2013, 2023) employ a similar strategy to study the diffusion of broadband internet in Norway, identifying firm-specific timing based on the largest change in local broadband coverage. We then restrict the sample to a symmetric window spanning three years before and three years after the event year. To maintain a balanced panel, we retain only those firms that are observed in all seven years of the event window.

We residualize all outcome variables of interest—including peer trade shocks ($\tilde{Z}_{imkt}$), output, employment, and productivity growth—on municipality fixed effects, time-varying sector fixed effects, and year fixed effects. In addition, we control for the firm's own trade shock Z_{imkt}, in order to isolate variation arising from differential exposure to global import demand shocks between the firm and its local peers.

A potential concern is that separations induced by negative demand shocks may not be

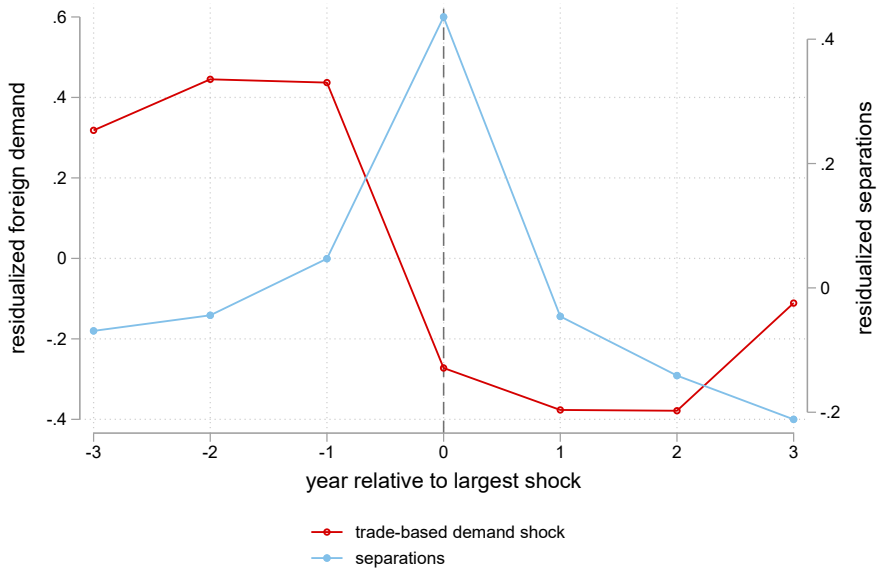
random, as firms might selectively retain or lay off workers based on unobserved characteristics. To address this, we control for the change in the average worker quality at the firm level, as proxied by estimated worker fixed effects. These fixed effects are obtained from a modified AKM model (Abowd et al., 1999), where we replace firm fixed effects with decile indicators for both firm size and lagged firm size, following the approach in Card et al. (2016). We compute the mean residuals of the estimated worker fixed effects across firms for each year relative to the event year. Including this control has negligible impact on our results, suggesting that separations do not systematically reflect selection on unobservable worker quality.

To further hone in on the mechanism highlighted in our model—namely, that new hires transmit productivity-relevant knowledge from their previous employers—we distinguish between shocks to peers with above- and below-median labor productivity. This stratification allows us to assess whether the productivity of the origin firm mediates the effect of worker mobility on the receiving firm's performance. Given our focus on the manufacturing sector, concerns about local demand spillovers are minimal. In contrast to service firms, Swedish manufacturing firms export the vast majority of their output (Akerman et al., 2013). Of the small share sold domestically, very little is directed toward buyers in the same municipality.

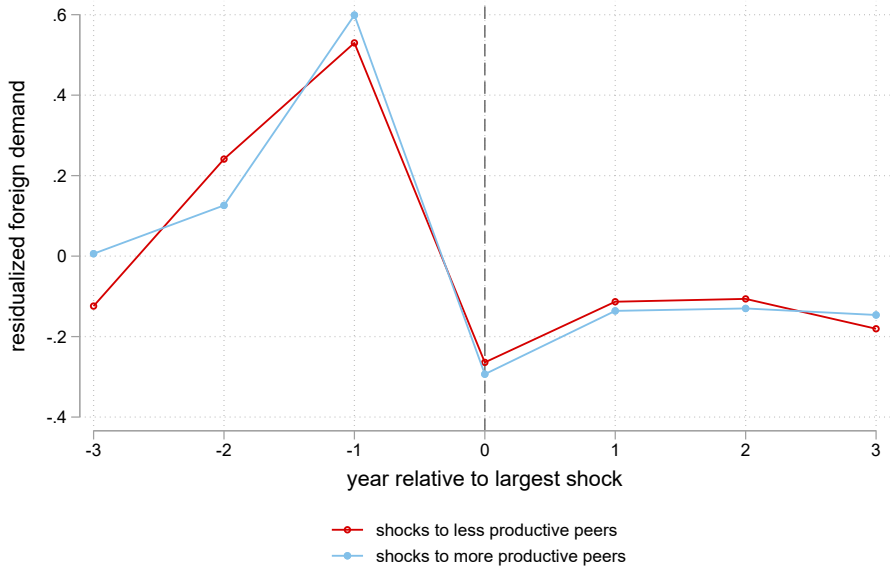
We begin our empirical analysis by examining the first stage: whether negative trade shocks increase the probability of separations within affected firms. Figure 4a plots the evolution of residualized Z_{jt} in the seven-year window centered on the firm-specific year of the sharpest decline in foreign demand. First, we observe that the event timing appears to capture significant exogenous variation. The drop in year 0 in the residualized foreign demand index is both pronounced and discontinuous. Second, in parallel, we document a sharp increase in the residualized probability of worker separations in the same year, followed by a return to baseline levels. In particular, a fall in import demand for a firm's products leads to an increase in separations. These patterns provide strong evidence that negative trade shocks induce involuntary worker mobility.

We next examine whether negative trade shocks to local peer firms—and the associated local labor supply shocks—affect hiring and productivity growth at the focal firm. Figure 4b illustrates the evolution of trade shocks to peers. As previously described, we distinguish between shocks to peers with above- and below-median labor productivity. The figure shows that the dynamics of trade shocks are strikingly similar across the two groups, which facilitates a clean comparison of subsequent outcomes across firms differentially exposed to workers from more versus less productive peers.

Figure 4: Shocks to foreign demand and separations



(a) Effect of foreign demand on separations



(b) Evolution of shocks to local peers

Notes: We construct an event-study framework by identifying, for each firm, the year in which it experiences the largest negative shock to world import demand for its products. This year is defined as the firm-specific event year. We then restrict the sample to a balanced panel covering the three years before and after the event year, retaining only firms observed in all years of the event window. To account for confounding trends, we residualize all relevant variables—specifically, firm-level trade shocks and separations—on municipality fixed effects and time-varying sector fixed effects. We then plot the average residualized outcomes across firms by event time. In panel b we plot firm-level trade shocks to peers—separately for peers with above- and below-median productivity.

Figure 5 presents the evolution of the key outcome variables. For ease of interpretation, we plot the difference in residualized outcomes between firms exposed to shocks affecting more productive peers and those exposed to shocks affecting less productive peers. A rise in the gap between years $t-1$ and t therefore reflects an increase in the differential response between the two groups.

We first observe that hiring increases following a positive local labor supply shock—that is, when local peers experience a negative demand shock. Importantly, the increase in hiring is larger when the shock affects more productive peers, consistent with the notion that such workers bring more valuable knowledge. Similarly, we find that productivity growth—measured as the annual change in log labor productivity—rises more when workers are released from more productive firms compared to less productive ones. This pattern aligns closely with the theoretical prediction that the productivity of the origin firm shapes the knowledge embedded in mobile workers.[15]

5.2 Separations by sudden and unexpected death

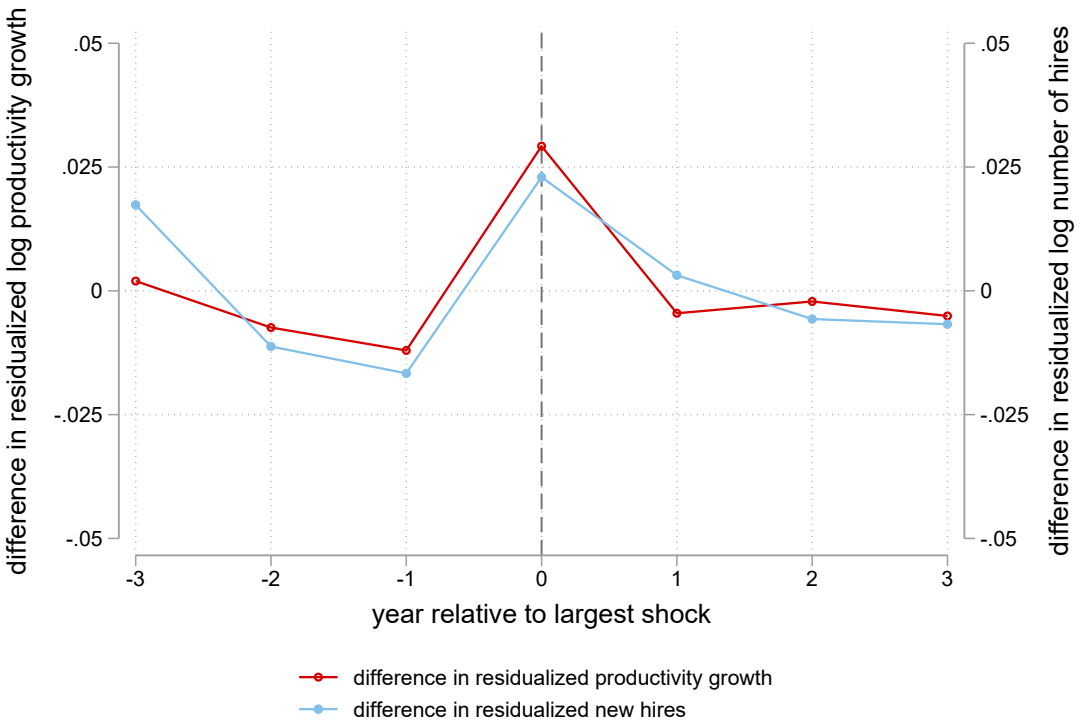
A natural approach to estimating the causal effect of worker separations is to implement an event study around exogenous worker deaths and assess their impact on firm-level productivity outcomes. In our set-up, we leverage past observed worker experience as a proxy for worker knowledge. We then leverage our model's predictions on product choice to bring together variation in worker knowledge with variation in firm product choice.[16]

Our dataset allows us to track the full employment history of each worker, enabling us to identify their prior experience with specific product lines based on the production activities of their former employers. For instance, if a worker was previously employed at a firm that produced a particular type of circular glass bottle, we classify that worker as having experience in producing that product. This rich information enables a direct test of knowledge effects: we examine whether the unexpected loss of a worker with given experience reduces the likelihood that the firm subsequently enters production of that product.

[15] Figure 5 focuses on changes in the levels of productivity. To calibrate our model, we also replicate the analysis using a binary indicator for whether a firm experiences any productivity growth. This alternative outcome captures changes in the probability of productivity improvement and is presented in Appendix Figure A.8.

[16] The model implies a mapping from productivity levels to specific product lines. Prior experience in firms producing a given product line hence indicates potential transmission of this knowledge level when hired. As a result, separations that disrupt (and reduce) firm productivity reduce the likelihood that the hiring firm expands within the same product line.

Figure 5: Evolution of hiring patterns and productivity growth during a local labor supply shock.



Notes: We construct an event-study framework by identifying, for each firm, the year in which its local peers—defined as firms in the same municipality and sector—experience the largest negative shock to world import demand for their products. This firm-specific year is designated as the event year. We restrict the sample to a balanced panel spanning three years before and after the event year, retaining only firms observed in all seven years. We then residualize firm-level hiring probabilities and annual changes in log labor productivity—separately for shocks to high- and low-productivity peers—on municipality fixed effects, time-varying sector fixed effects, and the firm's own trade shock. This approach isolates variation in peer shocks while controlling for firm-level exposure to global demand. The figure plots the difference in mean residualized outcomes across firms between high- and low-productivity peer shocks for each year relative to the event.

We estimate this regression at the firm–product–year level, where the outcome variable is a binary indicator equal to one if firm i begins producing product j in year t.[17] The key explanatory variable captures whether the deceased worker had prior experience producing the specific product in question. To account for variation in treatment intensity, we calculate the number of years the deceased worker was engaged in producing product j and interact this experience measure with event-time indicators.

The corresponding regression specification is:

$$X_{ijt} - X_{ij,t-1} = \sum_{\tau=t-3}^{t+3} \alpha_\tau \times I_{\text{period}_\tau} \times \text{years}_{ij} + \gamma_{ij} + \eta_t + \varepsilon_{it} \tag{9}$$

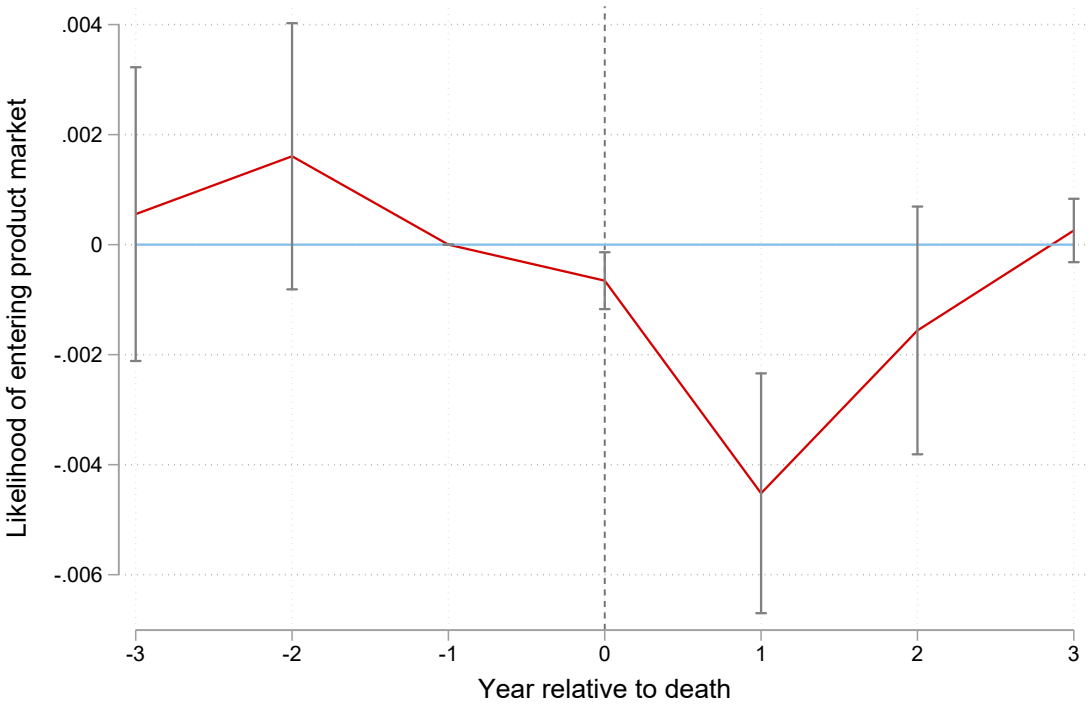
where X_{ijt} equals 1 if firm i produces product j in year t, and years_{ij} denotes the number of years of prior experience the deceased worker had in producing product j. The specification includes firm–product fixed effects γ_{ij} and year fixed effects η_t, and controls for contemporaneous firm-level employment. This framework allows us to identify whether the loss of specific product knowledge affects a firm's probability of expanding into related product lines.

Figure 6 presents the results of the event-study analysis on horizontal productivity. The pre-event period is characterized by parallel trends, supporting the identifying assumptions of the design. At the time of the death event, we observe a small but statistically significant decline in the probability of entering a new product line. This effect becomes substantially larger in the first year following the event. While the effect dissipates by the second year, the decline is not reversed in subsequent periods, suggesting that the shock has persistent consequences. Specifically, we estimate that an unexpected worker death reduces the likelihood of product entry by approximately 0.4 percentage points—equivalent to about one-fifth of the baseline probability of product entry among the affected firms. In Appendix Figure A.3, we restrict the sample to firms that do not replace the deceased worker during the event window. The results are similar in magnitude and significance.

Although our identification strategy is based on worker exits rather than hires, we interpret these results as reflecting the productive value of knowledge—knowledge that firms potentially acquire when hiring a worker. In this setting, product entry serves as a proxy for the utilization of such knowledge, with the event-study capturing the firm's reduced capability to leverage that expertise following an unanticipated separation.

[17] Most firms in our sample experience only one worker death. In 174 cases, however, firms experience two deaths at different points in time; we treat these as distinct events.

Figure 6: 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.

To further investigate the observed effects , we explore heterogeneity by educational attainment. In Appendix Table A.6, we regress the probability that a firm begins producing a particular product on the cumulative product-specific experience of workers who die unexpectedly in the prior year conditional on worker education. We estimate this regression separately for workers with and without a university degree. The results show that the negative effects of unexpected deaths are significantly larger for more highly educated workers. We interpret this result in light of our theory as a larger loss given a larger initial knowledge level (given the loss is αP in the theory).

In Appendix Table A.7, we replicate the analysis using product-level sales as the outcome. Again, we find that the loss of product-specific experience due to worker deaths negatively affects firm-level sales, with substantially larger effects following the deaths of more educated

workers.

To summarize, the empirical evidence presented in this section demonstrates that worker mobility, when induced by plausibly exogenous events, has meaningful effects on firm-level outcomes. We find that such mobility shapes firms' growth potential, particularly when it involves more educated and experienced workers. These findings provide strong motivation for estimating the quantitative effect of worker mobility events on aggregate growth.

6 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 6.1, before proceeding to show the empirical results in section 6.2. After presenting parameter estimates and the growth decomposition into parts deriving from mobility and innovation, we present a model application in section 6.3.

6.1 Calibration argument

The productivity distribution for Swedish firms, as shown in Figure 7, indicates a noticeable rightward shift over time. In this section, we illustrate how the model equations quantify the role of labor mobility in shaping the average shift of the productivity distribution over time. Specifically, we rely on the two equilibrium conditions, recast as equations 10 and 11, which characterize equilibrium unemployment u and economic growth γ as functions of labor market and idea distribution parameters.

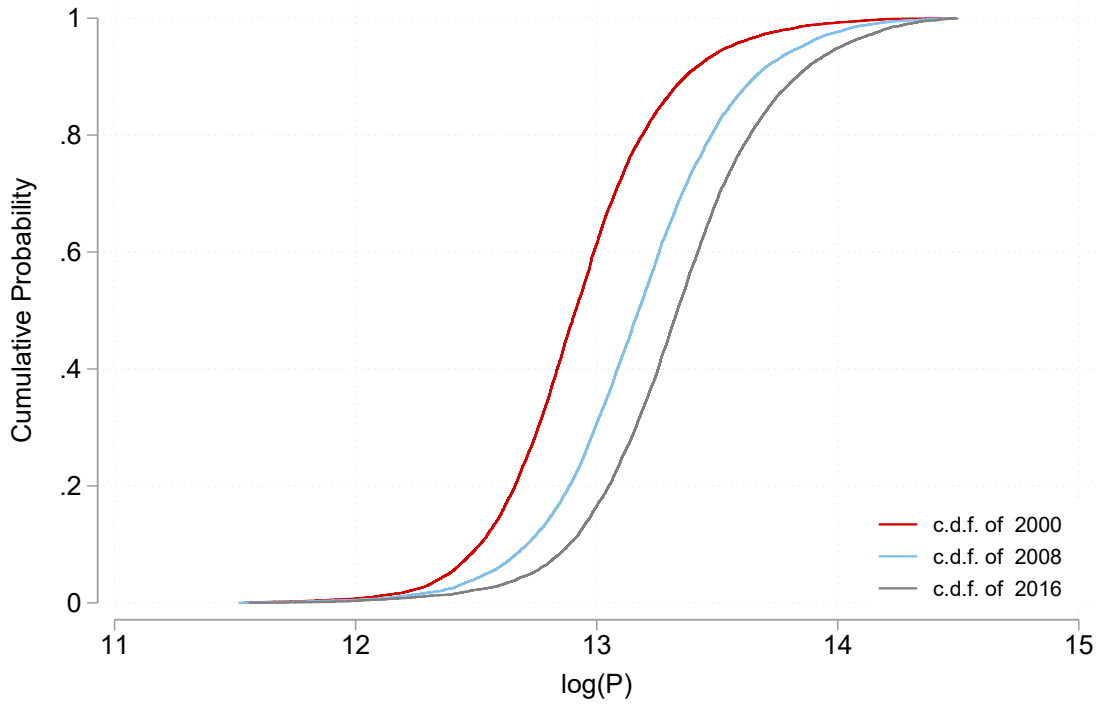
$$\delta \frac{k_\Theta}{k_\Phi} = \lambda + \frac{\gamma}{\eta_p \theta} + \frac{\mu_w N^I}{N^J} \omega \alpha_\Pi \tag{10}$$

$$\gamma = \theta \left(\omega \lambda \left(\frac{k_\Phi}{k_\Theta} u + s(1-u) \right) + \beta \alpha_\Upsilon \frac{k_\Phi}{k_\Theta} + \mu_f + \delta \left(\alpha^{\frac{1-\theta}{\theta}} - 1 \right) \right) \tag{11}$$

Our goal is to pin down the labor market parameters and long-run idea distribution parameters such that they are consistent with a long-run balanced growth path of which we observe the characteristic growth rate γ and unemployment rate u.

We calibrate the model by leveraging firm productivity and worker mobility data from our Swedish data sample. Specifically, we use firm-level data on four economic measures. First, we use average worker productivity $P = Y/N$, obtained as (revenue-based) value-added per worker. Second, we incorporate worker mobility events, capturing whether firms

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.

experience a worker arrival—including labor market entrants, hires from unemployment, or job-to-job transitions—or a worker departure. Information on worker death events allow us to isolate unexpected departures. Third, we use firm-level R&D expenditure data. Finally, to control for revenue-based fluctuations in productivity, we include demand shocks instrumented using shift-share methods following Hummels et al. (2014). Since our focus is on the long-run balanced growth path, these instruments help isolate demand-driven variations outside the scope of our model.

The calibration of labor market parameters mostly follows standard practices and leverages worker mobility 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 such that $E_\Theta[EU] = \hat{\delta}$, where the subscript Θ denotes averages over the firm distribution. Similarly, we estimate $E_\Theta\left[\frac{N^I(1-u)}{N^J}\right] = \hat{f}$, and we estimate UE and EE from UE and EE mobility events as firms' likelihood of experiencing such a worker entry 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.[18]

To pin down the remaining idea distribution parameters, we bring together the microeconomic data on worker mobility events and firm productivity trajectories. We begin by identifying productivity losses associated with worker mobility, denoted by α, where a worker's exit to unemployment reduces productivity to αP. To estimate the skill depreciation parameter α, we regress current firm-level productivity on its lagged value, allowing for a differential slope among firms experiencing an exogenous 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 α using the regression specification

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

where ε denotes simple measurement error and x denotes the 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 while allowing for empirical covariates. As covariates we chose current and lagged output.

Second, we 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

[18]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.3.1.

might depend on observable characteristics. We hence estimate Prob{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 as

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

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. We specialize the productivity distributions, indexed by letter D for $D \in \{\Pi, \Upsilon\}$, as Pareto distributions with countercumulative distribution function $\text{Prob}(X > x) = \kappa^{1/\theta} x^{-1/\theta}$.[19] In the absence of worker mobility, the model predicts productivity increases through innovation at rate $\bar{\Upsilon}(P,t)$, such that

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

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

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

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

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

respectively. Together, these three equations imply a regression specification for estimating θ, based on the likelihood of productivity changes averaged over productivity levels P and time t. This yields a set of observations indexed by $n = 1, \ldots, N$, 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.

[19] Note that given this parameterization, $k_D = \kappa_D^{1/\theta}$ for the two distributions $D \in \{\Pi, \Upsilon\}$ of new ideas through innovation (Υ) and the distribution of new workers (Π).

Finally, we can estimate the parameter ω, the likelihood of knowledge adoption upon hiring, as the average likelihood of a productivity increase upon a EE hire, $\mathbb{E}_\Theta[\text{Prob}\{\Delta P > 0|\text{EE \& No Innov.}\}]$. Given the functional form assumption for the firm productivity distribution, $\mathbb{E}_\Theta[\text{Prob}\{\Delta P > 0|\text{EE \& No Innov.}\}] = \hat{\omega}/2$, as shown in Appendix section A.3.

Using this calibration strategy, we can recast the two equilibrium equations 10 and 11 as (cf. Appendix section A.3.2 for derivation)

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

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

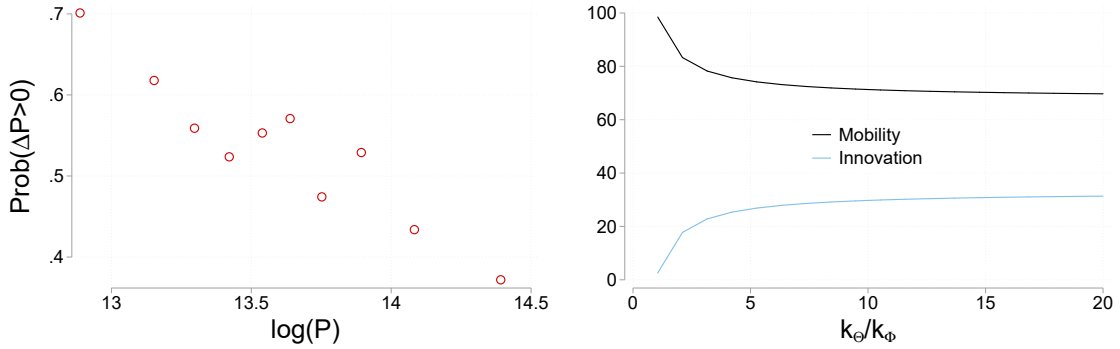
We can see that the equations relate parameter estimates to the growth rate γ, the unemployment rate u and the relative efficiencies of innovation sources α_Π and α_Υ as well as the ratio of productivity distribution intercepts $\frac{k_\Phi}{k_\Theta}$. Given the calibrated parameters and the unemployment rate and growth rate, we are hence left with three unknowns and two equations. To ensure full transparency of our results, we will discuss results for different values of $\frac{k_\Phi}{k_\Theta}$ (and their implied values for α_Π and α_Υ).

6.2 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, ω 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 panel a contains a graphical representation of the estimation results for the productivity distribution parameter θ. We find an estimate for θ of 0.76. We can compare our estimate to the values used in Lucas and Moll (2014), who consider θ between 0.5 and 0.8 for the US economy. Since $1/\theta$ corresponds to the tail parameter of the idea distribution, our estimate implies a fatter tail (i.e., a smaller tail parameter) relative to their values. This would suggest a higher variance in the productivity distribution of Swedish manufacturing firms compared to the US—potentially reflecting greater heterogeneity in productivity across firms. We further 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). For the knowledge adoption rate ω, we find a value of 0.91, such that 91% of meetings with a potential knowledge adoption also yield a productivity upgrade. There is no other study that allows us to compare estimates, but we recall that this estimate derives from the likelihood of productivity growth after a E2E hire at firms without innovation. As we find a low value for the innovation rate, this estimate reflects the fact of non-negligible economic growth even in the absence of innovative activity. To shed more light on the knowledge adoption parameter, we estimated ω separately by the type of worker that was hired (assuming a fully segregated economy). We find that ω is higher for hires from top decile occupations (0.92) as compared to below median occupations (0.90).

Figure 8: Parameter Estimates and Growth Decomposition



(a) Parameter Estimates

(b) Growth Decomposition

Notes: Panel A 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. Panel b 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.

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.9 in the Appendix.[20]

[20]We here make use of the mapping

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

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

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 $\alpha_\Upsilon > \alpha_\Pi$ (for all $\frac{k_\Phi}{k_\Theta} > 5$) , such that the distribution of new ideas has a higher mean than the distribution of skills of new labor market entrants, as expected. Differently put, we consider values of $\frac{k_\Phi}{k_\Theta} > 5$ as the empirically relevant range.

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 12.

$$\gamma = \overbrace{\omega\theta UE\frac{k_\Phi}{k_\Theta} + \omega\theta EE}^{\text{Mobility}} + \overbrace{\theta\beta\alpha_\Upsilon\frac{k_\Phi}{k_\Theta}}^{\text{Innovation}} + \overbrace{\theta\delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right)}^{\text{Displacement}} + \overbrace{\theta(UE-\delta)\frac{(1-u)}{f}}^{\text{New Firms}} \tag{12}$$

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 0.002 percentage points (or 7.4% of the estimated aggregate average growth rate). To place our results in broader context, we consider the implications of changes in employment protection legislation (EPL) for aggregate growth via their effect on worker mobility. Estimates from OECD (2010) and Martin and Scarpetta (2011) indicate that a one-point increase in the OECD EPL index on regular employment —equivalent to the difference in the EPL index between Sweden and Australia in 2010 —reduces job-to-job mobility by approximately 2 percentage points.[21] Applying these estimates to our framework implies that a relaxation of Sweden's EPL would increase aggregate growth by 1.38 percentage points, holding other factors constant.

The total effect of mobility on growth, including mobility from unemployment, depends 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 8 panel b. Overall, we find that worker mobility accounts with over 60% for the majority of economic growth. Our result finds resonance in Liu (2023). While featuring a different setting, Liu (2023) reports that worker mobility accounts for 61% of TPF growth. In appendix section A.4 we show how changes to parameters affect the growth share. There we show that a larger tail of the firm productivity distribution $1/\theta$ lowers the importance of worker mobility for growth and a higher value for knowledge adoption ω increases the contribution. Specifically, at $\theta = 0.3$, worker mobility accounts for

[21] In 2010, Sweden featured an EPL index of 2.61, above the OECD average of 2.15, with Australia featuring an EPL index of 1.67. Source: OECD ELP Index 2010.

33% of growth. In the range of values considered by Lucas and Moll (2014) (0.5 and 0.8), the growth contribution is over 50%.

We relate our findings to the empirical evidence presented in section 4 by conducting a variance decomposition of labor productivity growth across sectors, presented in Table 6, Panel A. In the cross-section, the decomposition reveals that worker mobility accounts for the majority of productivity growth, with the effect being particularly pronounced when restricting the sample to mobility among workers in the top decile of the income distribution. While the empirical and theoretical approaches do not map one-to-one, this analysis provides additional support for the conclusion that labor mobility plays a dominant role in explaining aggregate productivity growth. Given the theoretical importance of knowledge adoption rates, we extend the analysis in Panel B of Table 6 by examining how variation in human resources (HR) practices correlates with the role of labor mobility in sectoral productivity growth. Specifically, we divide the sample into equally sized groups based on the sectoral share of workers employed in human resource (HR)-related occupations, identified using occupational codes. Our classification focuses specifically on HR managers (levels 1 and 2) and personnel and HR specialists, corresponding to SSYK codes 1221, 1222, and 2423. The results indicate that sectors with a higher share of HR workers exhibit a larger portion of productivity growth variance explained by labor mobility. These findings suggest that managerial practices—particularly those related to human capital management—may directly influence productivity growth, for instance via more effective worker on-boarding.

6.3 Analysis of Growth Determinants

We now consider an application of our framework regarding 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 estimate of job-to-job hiring rate at the firm level over our sample period in Sweden, cf. Figure A.10 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

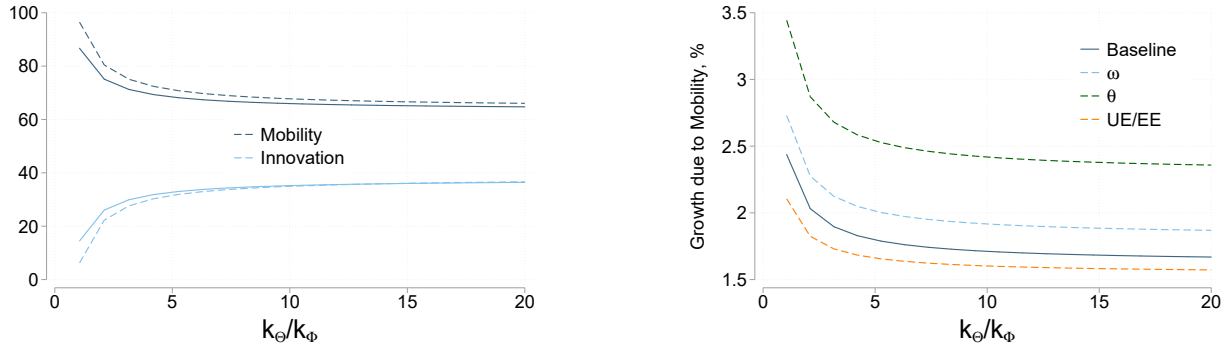
Table 6: Share of variation in productivity growth explained by mobility versus innovation.

Dep. var: productivity growth		
	Category of occupations	
Panel A: By occupation charact.	Bottom half	Top ten percent
Factor		
EE mobility	54%	83%
R&D	20%	35%
Covariance	39%	1%
	HR staff	
Panel B: By sector charact.	Less	More
Factor		
EE mobility	4%	34%
R&D	68%	36%
Covariance	29%	30%

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 denote the shares in percent that each factor explains out of total variation explained.

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, knowledge adoption ω and overall growth γ are found to be higher in the post as compared to the pre-period. The left panel of Figure 9 indicates that, according to these estimates, labor mobility contributed less to aggregate growth in Sweden after 2009. Nevertheless, labor mobility accounts for the majority of economic growth over both sample periods. To put these sample differences in more perspective, the right panel of Figure 9 shows a counterfactual exercise where we adjust only a single parameter and consider its effect on growth. We find that the drop in mobility rates (orange dashed line) contributed relatively little to the drop in economic growth due to mobility. We find that its change is more than offset by the rise in the knowledge adoption rate ω (light blue line). Moreover, the increase in θ had the largest effect. These results suggest that he decline in labor mobility was offset by better availability of high productive ideas (θ) and improved knowledge absorption (ω). This analysis offers a more favorable interpretation of the recent decline in labor mobility when viewed in conjunction with concurrent shifts in the parameters governing knowledge transmission. The findings further underscore the central role of knowledge adoption in the transmission mechanism, suggesting it as a potential lever for private sector firms seeking to mitigate the adverse implications of reduced worker mobility, potentially through favorable HR practices.

Figure 9: Subsample and Counterfactual Analysis



Notes: The left figure shows a graphical representation of the growth share due to worker mobility or innovation given $\frac{k_\Phi}{k_\Theta}$. The dashed line represents the decomposition for the period before 2009 whereas the solid line represents estimates after 2009. The right figure shows a counterfactual exercise showing the percentage growth rate due to worker mobility, allowing selected variables to differ. Baseline denotes the set of parameters for years before 2009, all other lines denote a change in one single parameter to the level of after 2009, holding all other parameters at before 2009 levels.

7 Conclusion

In this paper, we provide both theoretical and empirical evidence that worker mobility affects firm growth. First, we develop a random search model on a balanced growth path to quantify the relative impact of worker mobility and R&D on aggregate productivity growth. Second, using highly granular data on workers and firms in Sweden, we document aggregate and microeconomic correlations between worker mobility and labor productivity growth, distinguishing between horizontal and vertical productivity gains. In a calibration exercise at the aggregate level, we find evidence that both worker mobility and R&D shape firm productivity growth.

While our analysis is conducted in a partial equilibrium framework without endogenous hiring, due to the assumption of constant returns to scale in production, it would be valuable to explore the implications under decreasing returns to scale with endogenous vacancy posting. Such an extension would challenge several aspects of the tractability of our model, including the affine representation of surplus, the closed-form balanced growth equation, and the ability to track the productivity distribution independently of firm size. Our preference for analytical simplicity is further motivated by the observation that, in such an economy, decreasing returns to scale could potentially constrain the adoption of more productive technologies, which is not essential to our core argument and mechanism. More importantly, if firms increase their hiring after innovating, thereby potentially hiring from more productive firms, innovation triggers further knowledge growth through mobility, which would likely strengthen

our decomposition results presented in section 6. Hence, we consider that our results can be considered as lower bounds for the amplification mechanism of worker mobility on growth.

In our setting, we further consider firms' innovation intensity as fixed. It would be valuable to relax this restriction to study firms' innovation incentives in light of worker mobility, which could dilute the expected returns to innovation in some settings. Such an approach would be well-suited to analyzing the implications of contractual mechanisms like non-compete agreements, as examined in Liu (2023). While these contractual arrangements are certainly relevant in the setting of the US economy, we argue that they are less of an empirical phenomenon in the Swedish manufacturing sector.

Our findings carry significant implications for the understanding of productivity growth, particularly in the context of the observed decline in worker mobility across firms and geographic regions in recent decades, as well as persistent cross-country differences in mobility rates. Holding other factors constant, the model predicts that reduced labor mobility leads to a decline in aggregate productivity growth. This result bears important policy relevance: labor market institutions—such as employment protection legislation that dampens worker mobility—may exert a direct negative impact on aggregate productivity, independent of their effects on firms' incentives to invest in R&D, as emphasized in Aghion et al. (2023).

References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

Aghion, Philippe, Antonin Bergeaud, and John Van Reenen, "The Impact of Regulation on Innovation," *American Economic Review*, November 2023, *113* (11), 2894–2936.

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood, "Buy, Keep, or Sell: Economic Growth and the Market for Ideas," *Econometrica*, 2016, *84* (3), 943–984.

Akerman, Anders, Elhanan Helpman, Oleg Itskhoki, Marc-Andreas Muendler, and Stephen Redding, "Sources of Wage Inequality," *American Economic Review*, 2013, *103* (3), 214–19.

Andersen, Steffen and Kasper Meisner Nielsen, "Participation Constraints in the Stock Market: Evidence from Unexpected Inheritance Due to Sudden Death," *The Review of Financial Studies*, 2011, *24* (5), 1667–1697.

Arora, Ashish, Sharon Belenzon, Andrea Patacconi, and Jungkyu Suh, "The Changing Structure of American Innovation: Some Cautionary Remarks for Economic Growth," *Innovation Policy and the Economy*, 2020, *20*, 39–93.

Audoly, Richard, "Firm Dynamics and Random Search over the Business Cycle," Technical Report 2023.

Baksy, Aniket, Daniele Caratelli, and Niklas Engbom, "The Long-term Decline of the US.S. Job Ladder," Technical Report 2024.

Balke, Neele and Thibaut Lamadon, "Productivity Shocks, Long-Term Contracts, and Earnings Dynamics," *American Economic Review*, 2022, *112* (7), 2139–77.

Bárány, Zsófia L. and Kerstin Holzheu, "The Two Faces of Worker Specialization," Technical Report 2024.

Bartelsman, Eric J., Pieter A. Gautier, and Joris De Wind, "Employment Protection, Technology Choice, and worker allocation," *International Economic Review*, 2016, *57* (3), 787–826.

Becker, Sascha O and Hans K Hvide, "Entrepreneur Death and Startup Performance*," *Review of Finance*, 05 2021, *26* (1), 163–185.

Benhabib, Jess, Jesse Perla, and Christopher Tonetti, "Reconciling Models of Diffusion and Innovation: A Theory of the Productivity Distribution and Technology Frontier," *Econometrica*, 2021, *89* (5), 2261–2301.

Bennedsen, Morten, Francisco Pérez-González, and Daniel Wolfenzon, "Do CEOs Matter? Evidence from Hospitalization Events," *The Journal of Finance*, 2020, *75* (4), 1877–1911.

Bernard, Andrew B., Stephen J. Redding, and Peter K. Schott, "Multiple-Product Firms and Product Switching," *American Economic Review*, March 2010, *100* (1), 70–97.

Bertheau, Antoine, Pierre Cahuc, Simon Jaeger, and Rune Vejlin, "Turnover Costs: Evidence from Unexpected Worker Separations," *Working Paper*, 2022.

Bhuller, Manudeep, Domenico Ferraro, Andreas R Kostøl, and Trond C Vigtel, "The Internet, Search Frictions and Aggregate Unemployment," Working Paper 30911, National Bureau of Economic Research 2023.

_ , Tarjei Havnes, Edwin Leuven, and Magne Mogstad, "Broadband Internet: An Information Superhighway to Sex Crime?," *The Review of Economic Studies*, 04 2013, *80* (4), 1237–1266.

Bilal, Adrien, Niklas Engbom, Simon Mongey, and Giovanni L. Violante, "Labor Market Dynamics When Ideas are Harder to Find," Working Paper 29479, National Bureau of Economic Research November 2021.

_ , _ , _ , and _ , "Firm and Worker Dynamics in a Frictional Labor Market," *Econometrica*, 2022, *90* (4), 1425–1462.

Bradley, Jake and Axel Gottfries, "Labor market Dynamics and Growth," Technical Report 2022.

Brooke, Hannah Louise, Mats Talbäck, Jesper Hörnblad, Lars Age Johansson, Jonas Filip Ludvigsson, Henrik Druid, Maria Feychting, and Rickard Ljung, "The Swedish cause of death register," *European Journal of Epidemiology*, 2017, *32* (9), 765–773.

Buera, Francisco J. and Ezra Oberfield, "The Global Diffusion of Ideas," *Econometrica*, 2020, *88* (1), 83–114.

Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women," *Quarterly Journal of Economics*, 2016, *131* (2), 633–686.

Carlsson, Mikael and Oskar Nordstrom Skans, "Evaluating Microfoundations for Aggregate Price Rigidities: Evidence from Matched Firm-Level Data on Product Prices and Unit Labor Cost," *American Economic Review*, 2012, *102* (4), 1571–95.

Carrington, William J. and Bruce Fallick, "Why Do Earnings Fall with Job Displacement?," *Industrial Relations: A Journal of Economy and Society*, 2017, *56* (4), 688–722.

Da-Rocha, José-María, Diego Restuccia, and Marina Mendes Tavares, "Firing costs, misallocation, and aggregate productivity," *Journal of Economic Dynamics and Control*, 2019, *98*, 60–81.

Davis, Steven J. and John Haltiwanger, "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *The Quarterly Journal of Economics*, 1992, *107* (3), 819–863.

_ and _ , "Labor Market Fluidity and Economic Performance," NBER Working Papers 20479, National Bureau of Economic Research, Inc September 2014.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda, "Declining Business Dynamism: What We Know and the Way Forward," *American Economic Review*, May 2016, *106* (5), 203–07.

Engbom, Niklas, "Misallocative Growth," Technical Report 2023.

Fujita, Shigeru, Giuseppe Moscarini, and Fabien Postel-Vinay, "Measuring Employer-to-Employer Reallocation," American Economic Journal: Macroeconomics forthcoming.

Grübener, Philipp and Filip Rozsypal, "Firm Dynamics and Earnings Risk ," Technical Report 2024.

Gulyas, Andreas, "The Puzzling Labor Market Sorting Pattern in Expanding and Contracting Firms ," Technical Report 2024.

Harrigan, James, Ariell Reshef, and Farid Toubal, "Techies and Firm Level Productivity," Working Paper 31341, National Bureau of Economic Research June 2023.

Holzheu, Kerstin and Jean-Marc Robin, "Wage Bargaining and Wage Posting Firms," Technical Report 2024.

Hopenhayn, Hugo, , and Liyan Shi, "Knowledge Creation and Diffusion with Limited Appropriation," Technical Report 2020.

_ **and Richard Rogerson**, "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy*, 1993, *101* (5), 915–938.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang, "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, June 2014, *104* (6), 1597–1629.

Hyatt, Henry R. and James R. Spletzer, "The shifting job tenure distribution," *Labour Economics*, 2016, *41*, 363–377. SOLE/EALE conference issue 2015.

Jäger, Simon and Jörg Heining, "How substitutable are workers? Evidence from worker deaths.," mimeo 2019.

Jaravel, Xavier, Neviana Petkova, and Alex Bell, "Team-Specific Capital and Innovation," *American Economic Review*, April 2018, *108* (4-5), 1034–73.

Jarosch, Gregor, Ezra Oberfield, and Esteban Rossi-Hansberg, "Learning From Coworkers," *Econometrica*, 2021, *89* (2), 647–676.

Jones, Benjamin and Benjamin A. Olken, "Do Leaders Matter? National Leadership and Growth Since World War II," *The Quarterly Journal of Economics*, 2005, *120* (3), 835–864.

Kambourov, Gueorgui and Iourii Manovskii, "Occupational Specificity of Human Capital," *International Economic Review*, 2009, *50* (1), 63–115.

Klette, Tor Jakob and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 2004, *112* (5), 986–1018.

Kletzer, Lori G., "The Role of Sector-Specific Skills in Post displacement Earnings," *Industrial Relations: A Journal of Economy and Society*, 1996, *35* (4), 473–490.

Koenig, Michael, Jan Lorenz, and Fabrizio Zilibotti, "Innovation vs. imitation and the evolution of productivity distributions," *Theoretical Economics*, September 2016, *11* (3).

Kortum, Samuel S., "Research, Patenting, and Technological Change," *Econometrica*, 1997, *65* (6), 1389–1419.

Lentz, Rasmus and Dale Mortensen, "Labor Market Friction, Firm Heterogeneity, and Aggregate Employment and Productivity," 2022 Meeting Papers, BSE 2022.

Leonard, Jonathan S, "In the Wrong Place at the Wrong Time: The Extent of Frictional and Structural Unemployment," Working Paper 1979, National Bureau of Economic Research July 1986.

Lim, Zaneta, Karen Gibbs, James E. Potts, and Shubhayan Sanatani, "A review of sudden unexpected death in the young in British Columbia," *Canadian Journal of Cardiology*, 2010, *26* (1), 22–26.

Lise, Jeremy and Fabien Postel-Vinay, "Multidimensional Skills, Sorting, and Human Capital Accumulation," *American Economic Review*, August 2020, *110* (8), 2328–76.

Liu, Jignan, "Worker Mobility, Knowledge Diffusion, and Non-Compete Contracts," Technical Report 2023.

Lucas, Robert E. and Benjamin Moll, "Knowledge Growth and the Allocation of Time," *Journal of Political Economy*, 2014, *122* (1), 1–51.

Luttmer, Erzo G. J., "Selection, Growth, and the Size Distribution of Firms*," *The Quarterly Journal of Economics*, 08 2007, *122* (3), 1103–1144.

Martin, John P. and Stefano Scarpetta, "Setting It Right: Employment Protection, Labour Reallocation and Productivity," IZA Policy Papers 27, Institute of Labor Economics (IZA) May 2011.

Milgrom, Maor, "The Costs of Job Displacement and the Demand for Industry-Specific Human Capital," Technical Report 2023.

Mion, Giordano and Luca David Opromolla, "Managers' mobility, trade performance, and wages," *Journal of International Economics*, 2014, *94* (1), 85–101.

Moscarini, Giuseppe and Fabien Postel-Vinay, "Stochastic Search Equilibrium," *The Review of Economic Studies*, 2013, *80* (4 (285)), 1545–1581.

Mukoyama, Toshihiko and Sophie Osotimehin, "Barriers to Reallocation and Economic Growth: The Effects of Firing Costs," *American Economic Journal: Macroeconomics*, October 2019, *11* (4), 235–70.

Neal, Derek, "Industry-Specific Human Capital: Evidence from Displaced Workers," *Journal of Labor Economics*, 1995, *13* (4), 653–677.

OECD, "Employment outlook," *OECD Publishing*, 2010.

Parent, Daniel, "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics," *Journal of Labor Economics*, 2000, *18* (2), 306–323.

Parsons, Christopher and Pierre-Louis Vézina, "Migrant Networks and Trade: The Vietnamese Boat People as a Natural Experiment," *The Economic Journal*, 2018, *128* (612), F210–F234.

Perla, Jesse and Christopher Tonetti, "Equilibrium Imitation and Growth," *Journal of Political Economy*, 2014, *122* (1), 52–76.

Poschke, Markus, "Employment protection, firm selection, and growth," *Journal of Monetary Economics*, 2009, *56* (8), 1074–1085.

Postel-Vinay, Fabien and Jean-Marc Robin, "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 2002, *70* (6), 2295–2350.

Saez, Emmanuel, Benjamin Schoefer, and David Seim, "Payroll Taxes, Firm Behavior, and Rent Sharing: Evidence from a Young Workers' Tax Cut in Sweden," *American Economic Review*, 2019, *109* (5), 1717–63.

Sauvagnat, Julien and Fabiano Schivardi, "Are Executives in Short Supply? Evidence from Death Events," *The Review of Economic Studies*, 02 2023, p. rdad027.

Sorkin, Isaac, "Ranking firms using revealed preference," *The Quarterly Journal of Economics*, 2018, *133* (3), 1331–1393.

Stoyanov, Andrey and Nikolay Zubanov, "Productivity Spillovers across Firms through Worker Mobility," *American Economic Journal: Applied Economics*, April 2012, *4* (2), 168–98.

Tambe, Prasanna and Lorin M. Hitt, "Job Hopping, Information Technology Spillovers, and Productivity Growth," *Management Science*, 2014, *60* (2), 338–355.

Appendix A Online Appendix

The following online appendix assembles details for the extension of the model to allow for product choice (cf. section A.1), details on the derivations in the theoretical section (cf. section A.2), details on a sensitivity analysis (cf. section A.4) as well as additional details on the data set (cf. section A.5), empirical evidence (cf. section A.6) and estimation results (cf. section A.7).

A.1 Model Extension with Product Choice

The optimal labor allocation for a given firm is determined sequentially. Notice first that the wage level $\bar{w}_j$ does not affect the relative labor allocation across products, as wages are paid uniformly across all products. Firms rank products based on the minimum labor required to break even net of labor costs, which is given by:

$$\tilde{n}_{ij} = \frac{F_i}{A_j p_i}.$$

Starting with the product requiring the largest $\tilde{n}_{ij}$ (denoted as $\tilde{n}_{ij}^{\max}$), the firm evaluates the points of indifference between successive products. The labor threshold at which the firm is indifferent between producing product i and product k is given by:

$$N_{ikj}^{x} = \frac{F_k - F_i}{A_j(p_k - p_i)},$$

where i and k represent the products ranked by their break-even labor levels $\tilde{n}_{ij}$, with k featuring the higher $\tilde{n}_{ij}$. If this intersection point falls outside the feasible labor range, either $N_{ikj}^{x} > N_j$ or $N_{ikj}^{x} < 0$, the firm produces only one product. Otherwise, the firm allocates $N_j - N_{ikj}^{x}$ units of labor to the product with the largest $\tilde{n}_{ij}$, and the process repeats for the remaining products.

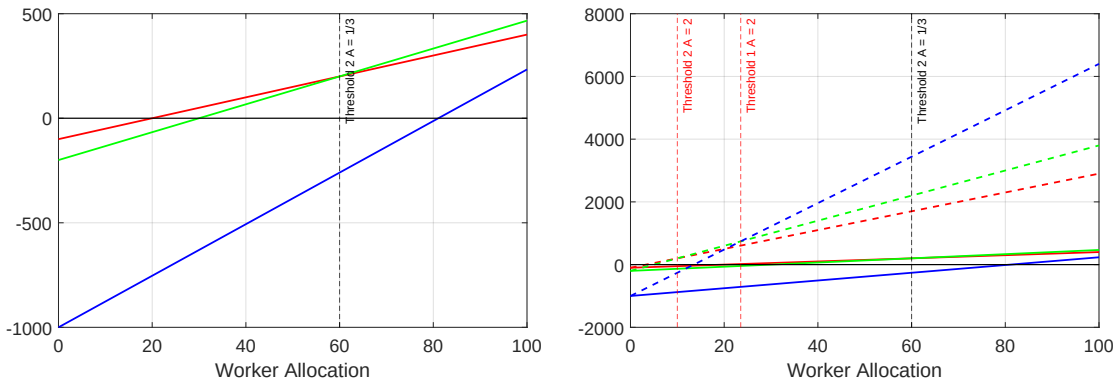
A general property of this framework is that an increase in firm productivity A_j raises the likelihood of product adoption. To see this, note that the minimum labor required to break even, $\tilde{n}_{ij}$, decreases with A_j. As productivity increases, more products can be produced while maintaining non-negative profits. Furthermore, the labor thresholds $N_{ik,j}^{x}$ that determine indifference points between product lines are also decreasing in A_j. This implies that as productivity rises, the firm becomes more likely to find it profitable to produce multiple products. Together, these mechanisms demonstrate that a higher A_j increases, on average, the number of products a firm chooses to produce.

Figure A.1a illustrates the solution for a case with three products by plotting the profit functions per product.[22] Figure A.1b shows the allocation when the firm's productivity increases to $A_j = 2$. This example demonstrates that an increase in firm productivity can lead to the production of a greater number of products. Specifically, in figure A.1a we see that

[22] Parameter values chosen for this figure are $A_j = \frac{1}{3}, p_1 = 15, p_2 = 20, p_3 = 37, F_1 = 100, F_2 = 200, F_3 = 1000, N_j = 100$.

the firm produces two products (green and red), delimited through Threshold 2, dividing the total workforce in a ratio 60:40. In Figure A.1b, firm productivity increases from $A_j = 1/3$ to $A_j = 2$. Labor allocations are now determined through Threshold 1 and Threshold 2 and a total number of three products is produced. The labor allocation switches towards a large share of workers producing the blue product.

Figure A.1: Profit functions per product and product choice



(a) Allocation Solution

(b) Change in Productivity

Notes: The figures illustrate the solution for labor allocations for products 1, 2 and 3 given parameters $A_1 = 1/3, A_2 = 2, p_1 = 15, p_2 = 20, p_3 = 37, F_1 = 100, F_2 = 200, F_3 = 1000, N_j = 100$.

A.2 Derivations

A.2.1 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

$$\begin{aligned}
&\Omega(P,N,t) = \Delta Y(P,N,t) + (1-\Delta r)[\\
&(EU \text{ Mobility}) + \Delta\delta\left(U(t+\Delta) + \Omega(\tilde{P}, N-1, t+\Delta)\right) \\
&(UE \text{ Mobility}) + (1-\Delta\delta)\Delta\lambda\left(\int_P^{\infty} \Omega(P', N+1, t+\Delta)dF(P',t) + \int_{\underline{P}}^{P} \Omega(P, N+1, t+\Delta)dF(P',t)\right) \\
&\qquad - (1-\Delta\delta)\Delta\lambda U(t+\Delta) \\
&(\text{Innovation}) + (1-\Delta\delta)(1-\Delta\lambda)\Delta\beta\left(\int_P^{\infty} \Omega(P', N, t+\Delta)dV(P,t) + \int_{\underline{P}}^{P} \Omega(P, N, t+\Delta)dV(P,t)\right) \\
&(\text{No change}) + (1-\Delta\delta)(1-\Delta\lambda)(1-\Delta\beta)\Omega(P,N,t+\Delta)] \qquad (13)
\end{aligned}$$

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 13 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.2.2 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 13. 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 13 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.2.3 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

$$\begin{aligned} rS(P,N,t) = R(P,N,t) + S_t + (\lambda - \delta)\, S_N + \delta S_{\tilde{P},P,N-1} \\ + \lambda \int_P^\infty S_{P',P,N+1} dF(P',t) + \beta \int_P^\infty S_{P',P,N} dV(P',t) \end{aligned} \tag{14}$$

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

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

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.2.4 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.2.5 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.2.6 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 a 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.2.1 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.2.7 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

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

with the corresponding substitutions $\hat{S}_t := \lim_{\Delta\to 0}\frac{\hat{S}(P,t+\Delta)-\hat{S}(P,t)}{\Delta}$, $\hat{S}_{P',P} := \hat{S}(P',t) - \hat{S}(P,t)$, $S_t^0 := \lim_{\Delta\to 0}\frac{S^0(P,t+\Delta)-S^0(P,t)}{\Delta}$, $S^0_{P',P} := S^0(P',t) - S^0(P,t)$. 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 14, 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.3 Knowledge Adoption Calibration

We aim to compute $\mathbb{E}_\Theta[\text{Prob}\{\Delta P > 0|\text{EE}\}]$ with

$$\text{Prob}\{\Delta P > 0|\text{EE}\} = \omega \kappa_\Theta^{1/\theta} x^{-1/\theta}$$

By the definition of the expectation given

$$f_X(x) = \frac{1}{\theta} \kappa_\Theta^{1/\theta} x^{-1/\theta - 1}, \quad x \geq \kappa_\Theta.$$

we obtain

$$\begin{aligned}
\mathbb{E}_\Theta[\text{Prob}\{\Delta P > 0|\text{EE}\}] = & \int_\kappa^\infty \text{Prob}\{\Delta P > 0|\text{EE}\} f_X(x)\, dx \\
= & \quad \omega \int_\kappa^\infty \left(\kappa_\Theta^{1/\theta} x^{-1/\theta}\right) \left(\frac{1}{\theta} \kappa_\Theta^{1/\theta} x^{-1/\theta - 1}\right) dx. \\
= & \quad \frac{\omega}{\theta} \kappa_\Theta^{2/\theta} \int_{\kappa_\Theta}^\infty x^{-2/\theta - 1}\, dx. = \frac{\omega}{2}
\end{aligned}$$

A.3.1 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.3.2 Estimation Equations

Given the two equilibrium equations

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

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

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

We rewrite the second equation as

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

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,

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

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

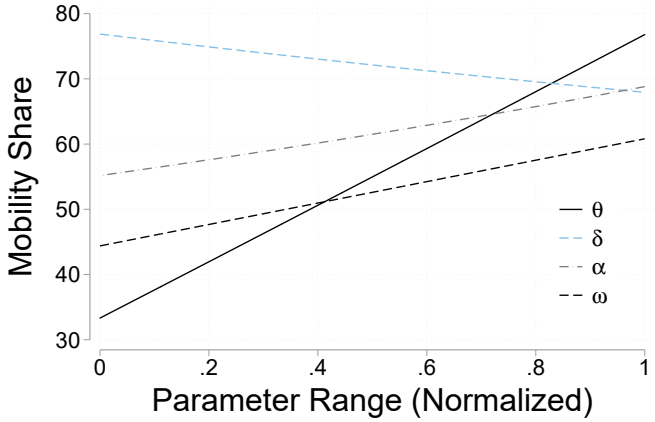
$$\alpha_{\Upsilon} = \frac{\left(\frac{\gamma}{\theta} - \omega UE\frac{k_{\Phi}}{k_{\Theta}} - \omega EE - \delta\left(\alpha^{\frac{1-\theta}{\theta}} - 1\right) - (UE - \delta)\frac{(1-u)}{f}\right)}{\beta\frac{k_{\Phi}}{k_{\Theta}}}$$

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

A.4 Sensitivity Analysis

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.2. In the figure, we vary the parameters θ, α, ω 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.2: 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] and ω: [0.7 1], with a normalization on the unit line.

displacement $1-\alpha$ reduces the contribution to growth emanating from worker mobility. Similarly, a higher adoption rate ω increases the growth contribution. The tail parameter of the productivity distribution is most impactful such that the importance of worker mobility increases sharply 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.5 Data Overview

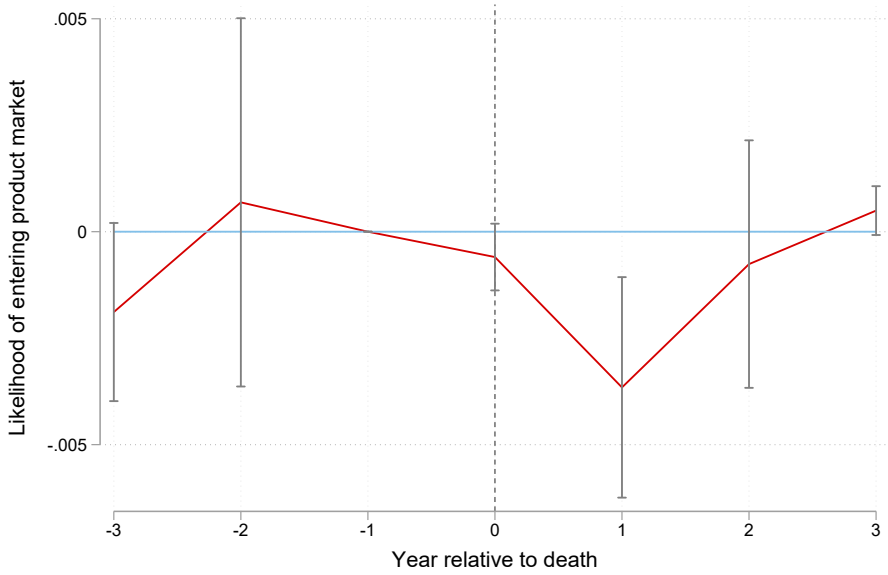
Table A.1: Variables across datasets

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

A.6 Additional Empirical Evidence

A.6.1 Trade shocks using TFP growth

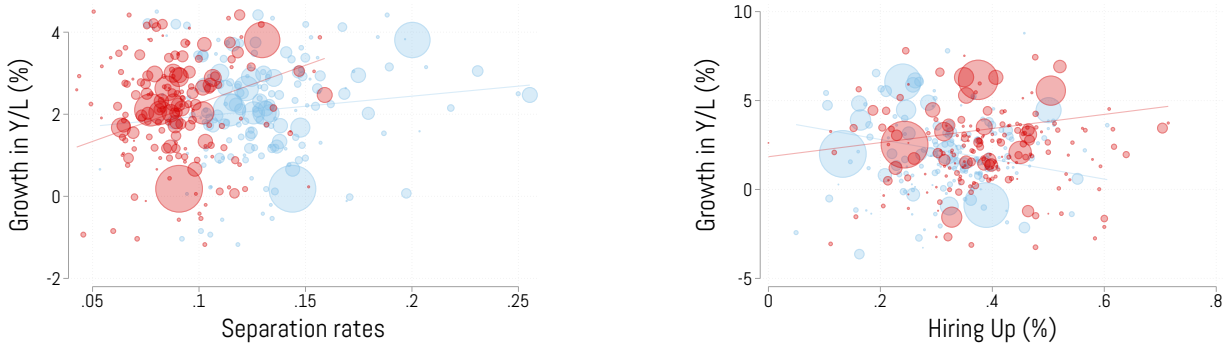
Figure A.3: Event study of death on product expansion



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.

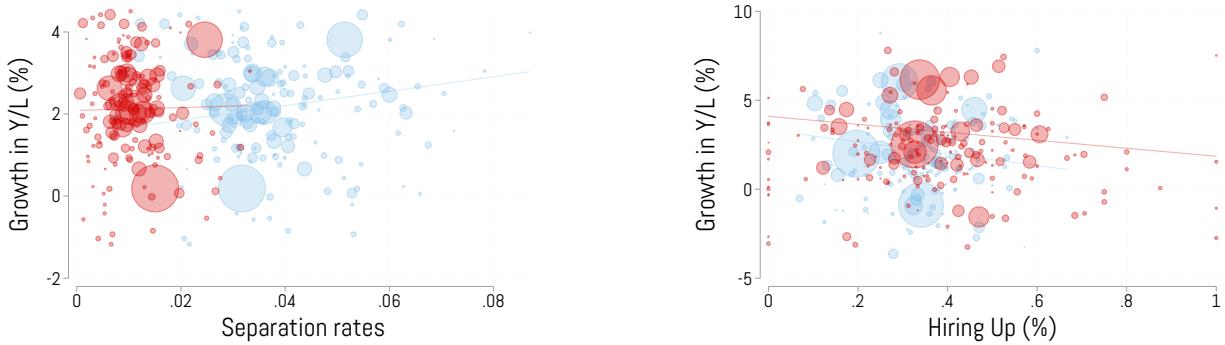
A.6.2 Regressions Motivation

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



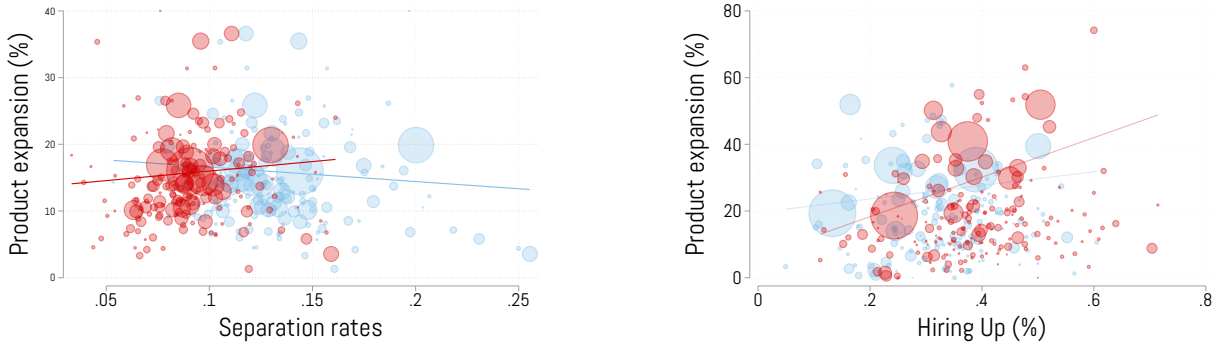
Notes: The left column shows binned scatter plots of the separation rate and the growth in labor productivity for occupations with below median wages (blue) and top decile occupations (red).The right hand side shows the share of workers who last worked at higher-productivity firms before entering the 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).



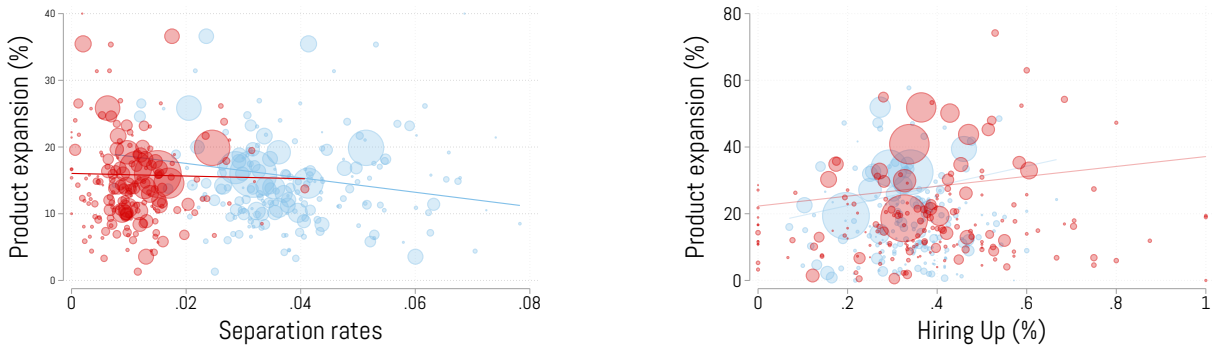
Notes: The left column shows binned scatter plots of the separation rate and the growth in labor productivity for occupations with below median wages (blue) and top decile occupations (red).The right hand side shows the share of workers who last worked at higher-productivity firms before entering the 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).



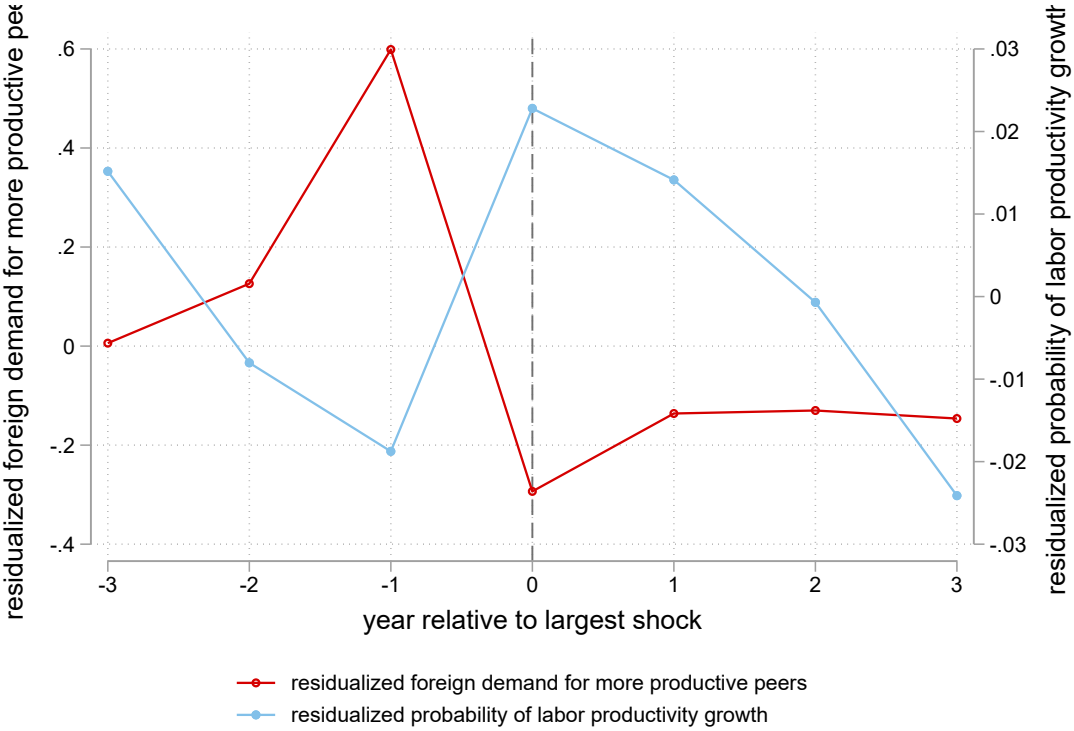
Notes: The left panel shows binned scatter plots of the separation rate and the likelihood of product expansion for all workers (blue) and top decile occupations as categorized by average earnings (red). The right hand side shows the share of workers who last worked at higher-productivity firms before 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.

Figure A.8: Evolution of productivity growth during a local labor supply shock



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 three years before and three 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 the foreign demand for the products of local high-productive peers and firm-level probabilities for increasing annual labor productivity and annual changes in log labor productivity, 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.

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.7 Estimation Result

A.7.1 Parameter Estimates and Data

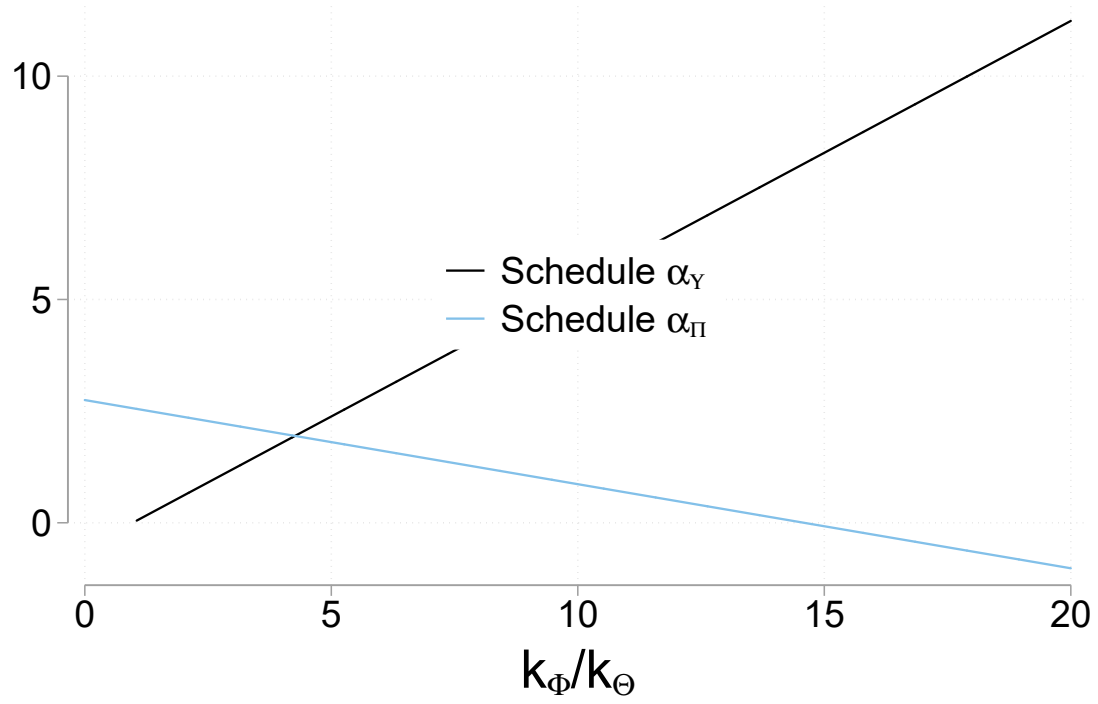
Table A.8: Estimated parameters and data

	Description	Value
	Innovation Parameters	
θ	PL exponent	0.76
α	Y/L- Disruption	0.97
β	Y/L- Innovation	0.02
ω	Knowledge Adoption	0.91
	Labor Market Parameters	
$\bar{N}^I(1-u)/\bar{N}^J$	Average Firm Size	50.91
UE	Job Arrival UE	0.013
EE	Job Arrival EE	0.027
δ	Job Displacement	0.022
	Empirical Data	
u	Unemployment Rate	0.072
γ	Growth Rate	0.028
Observations		242 380

Notes: The table shows parameter estimates together with the two equilibrium values unemployment rate u and growth rate γ.

A.7.2 Mobility patterns over time

Figure A.9: Innovation Intensities

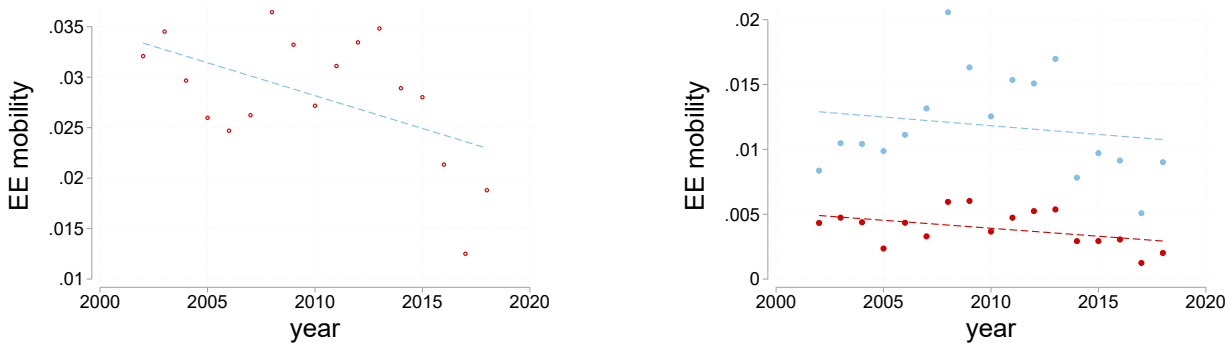


Notes: The figure shows a graphical representation of the two equations pinning down the estimated α_Υ, α_Π for a given $\frac{k_\Phi}{k_\Theta}$ and the set of the remaining parameter estimates. The two equations are

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

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

Figure A.10: 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
ω	Knowledge Adoption	0.91	0.86	0.96
	Labor Market Parameters			
$\bar{N^I}(1-u)/\bar{N^J}$	Average Firm Size	50.91	52.55	48.69
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
	Empirical Data			
u	Unemployment Rate	0.072	0.068	0.076
γ	Growth Rate	0.028	0.025	0.038
Observations		233 287	133 948	99 339

Notes: The table shows parameter estimates together with the two equilibrium values unemployment rate u and growth rate γ for the whole sample and two sub-sample analysis, once for the period before 2009 and once after 2009.