Does Mobility Beget Mobility? Coworker Networks and the Sectoral Reallocation of Labor

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Abstract

Social networks influence labor market outcomes. We investigate how the sectoral composition of an individual's current coworkers' past employment affects job-switching decisions. To identify causal effects, we employ multiple strategies, including distinguishing between current-year and non-current-year coworkers, controlling for time-varying shocks specific to the industry pairs, and using unexpected death or retirement events to isolate idiosyncratic changes in coworker networks. Using German administrative matched employer-employee longitudinal data, we find a positive causal relationship between the proportion of coworkers from a sector and both the propensity of transitioning to that sector and the sensitivity to sectoral wage changes. To quantify the coworker mechanism's contribution to employment and reallocation, we develop and estimate a multi-sector, multi-firm general equilibrium model where perceived wages and adjustment costs for sector transitions depend on coworker shares. Our results show that the welfare effect of COVID-induced productivity shocks is higher when considering coworker networks compared to assuming no influence from coworkers. Maintaining worker-employer ties to reduce competition in positively shocked sectors can further increase welfare.

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1 Introduction

Labor reallocation across sectors is crucial for both economic growth and individual welfare. However, sectoral labor allocation is sluggish.[1] Understanding the frictions that impede the speed and magnitude of labor market transitions across sectors is important for evaluating the effects of industrial policies and the economic prospects for displaced workers.

Labor mobility across sectors is often constrained not only by the costs associated with switching jobs but also by information barriers and uncertainties workers face when transitioning to unfamiliar fields. While traditional models emphasize sector-specific skills and relocation costs as primary obstacles, coworker networks provide a crucial, yet underexplored, avenue for overcoming these frictions. Through connections with current and former coworkers, individuals gain valuable insights into wages, job stability, and working conditions in other sectors—information that may otherwise be inaccessible. These networks serve as channels for sector-specific knowledge, help mitigate the perceived risks of moving into new industries, and offer practical support, such as referrals, that can facilitate entry into new fields. By incorporating coworker networks into the analysis of sectoral reallocation, this paper presents a framework for understanding labor mobility that accounts for both structural constraints and social mechanisms that may either reinforce or alleviate these barriers, thereby shaping labor responses to economic shocks.

We address three core questions about coworker networks, sectoral mobility, and labor reallocation. First, to what extent do the sectors in which a worker's current coworkers were previously employed causally influence the worker's future sectoral and firm choices? Second, how do these networks affect the propagation of economic shocks, influencing both individual mobility and aggregate labor outcomes? Finally, how effective are policies aimed at redirecting labor after productivity shocks when accounting for coworker networks? To answer these questions, we provide empirical evidence that the composition of one's current coworkers has a causal impact on sector transitions. We then estimate a structural model of job and sectoral choices under coworker influences to quantify the channels through which coworker networks operate and evaluate policies that limit labor mobility, such as short-term work arrangements.

Our paper begins by examining the empirical relationship between a worker's propensity to transition into another sector and the share of their current coworkers who were previously employed in that sector. Establishing causality is challenging, as standard datasets do not allow for the observation of an individual's complete coworker network. Moreover, many factors that influence a coworker's employment history may also affect the individual's likelihood of moving between sectors. To overcome these challenges, we use rich administrative data from Germany that contains workers' entire employment histories down to the exact day, allowing us to identify the complete employment history of all colleagues whose current employment overlaps with the individual of interest. We develop

[1] The U.S. economy, for instance, faces challenges in directing labor to sectors where it is most needed, such as the semiconductor (Washington Post 2023), the fiber optics (WSJ 2023) and the electrical industries (WSJ 2023).

and employ novel empirical strategies to isolate changes in one's coworker network compositions that are idiosyncratic from other factors which could simultaneously impact job choices.

We use three approaches to identify idiosyncratic changes in coworker composition. First, we distinguish *current-year coworkers* from *non-current-year coworkers*. Current-year coworkers – individuals who are employed at the firm during a certain reference year – make job choice decisions based on the concurrent barrier to transition between two industries, such as skills, distance, technological disparities, and cultural differences, and they can also disseminate information and skills to ease transitions. In contrast, non-current-year coworkers – those who are employed at the incumbent firm at some point in time but not during the current year – do not exert any additional influence over the transitional difficulty of their coworkers to their previous sector of employment due to their lack of interaction. By controlling for the shares of non-current-year coworkers and using only the difference between the current-year and the non-current year coworkers as the source of identifying variation, we minimize confounding factors and focus on the variations from the information and skills obtained through interaction with coworkers. Second, we include a comprehensive set of control variables, including various individual-level characteristics and industry pair-by-occupation-by-year fixed effects, to account for any time-varying shocks that affect labor transition difficulty between specific origin and destination industries, for each occupation.[2] Third, motivated by a large body of literature, we use coworker death and retirement events as exogenous sources of variation in workers' coworker networks and examine how sectoral choices vary before and after such events.[3]

Our findings indicate a positive, causal relationship between the share of coworkers from a sector and an individual's likelihood of moving into that sector.[4] Importantly, having more coworkers from a sector not only increases the average *propensity* of moving into that sector but also enhances the *elasticity* of this movement with respect to the predicted wage differential that workers could incur by moving to the destination industries. We also show that this relationship remains robust to alternative coworker definitions. Furthermore, it is consistent across gender, nationality, age, wage, and tenure distributions. Conditional on moving into a sector, workers with higher shares of coworkers previously employed in that sector are also more likely to move into higher-quality firms and stay at their new jobs longer.

The empirical results accommodate two mechanisms through which coworker networks operate. First, having more coworkers from a sector can help individuals improve their *skills or connections*

[2]The remaining variation in the imputed destination sector wage, at the occupation-by-location level, is relevant for individual decision-making as it captures localized wage opportunities that workers realistically face when considering a move. This variation reflects regional labor market conditions and ensures that the wage incentives modeled are pertinent to the worker's context. Given that these local wage differences are exogenous to unobserved factors influencing the decision to move, they provide a valid basis for estimating the causal effect of wage differentials on sectoral transitions. Robustness checks confirm that the results are not sensitive to this level of variation.

[3]Previous literature, including Jones and Olken (2005), Bennedsen et al. (2007), Azoulay, Graff Zivin and Wang (2010), Nguyen and Nielsen (2010), Andersen and Nielsen (2011), Oettl (2012), Jaravel, Petkova and Bell (2018), Becker and Hvide (2022), and Jäger and Heining (2022), has used death as a source of exogenous variation. Other works, such as Bianchi et al. (2023) and Boeri, Garibaldi and Moen (2022), rely on workers around the age of retirement for identification.

[4]This statement applies to the sample of all workers, job switchers only, and new hires only.

specific to that sector, thereby lowering the average difficulty of moving into the sector. Second, current coworkers can spread *information* regarding compensation levels in their previous sectors, consequently enabling their colleagues to understand better the outside options beyond their current sector and increasing the responsiveness of their decisions to move into those sectors based on wage differentials. Our subsequent analysis will be consistent with both mechanism and will not separate them.

We develop a dynamic framework of job and sector choices under coworker influence. In the model, each sector is subject to a sector-specific shock, and productivity at each firm consists of a firm-specific component and a sector-specific component shared across all establishments within that sector. At each time period, workers choose both the sector and the firm they want to be employed in, with their preferences for the non-wage characteristics of a job being correlated for firms within the same sector. The choice of job depends on workers' expected utility of being employed in each destination firm and the cost of transitioning into that firm. The moving cost has a time-varying component that is common to every employee within the same firm and an idiosyncratic component reflecting non-pecuniary preferences.[5] We extend standard dynamic discrete choice models for job choice, which assume perfect information on wages and exogenous bilateral job-switching costs to allow both the perceived productivity level—and therefore the expected wage and utility—and the cost of moving into a destination firm to depend on the contemporaneous share of current coworkers who were last employed in the sector to which the firm belongs. Despite endogenizing the influence of coworkers, our modeling framework allows for closed-form aggregation from individual-level decisions to bilateral job flows, similar to a standard dynamic nested logit model.

We structurally estimate the parameters in our model related to job and sector switching. In addition to the parameters standard in a nested sectoral choice model, our setup includes four key parameters that encapsulate the influence of coworker networks on job choice. At the sector level, one parameter describes how perceived sectoral TFP becomes more accurate as the share of coworkers from that sector increases, while the other relates coworker share to the reduction in transitional costs during that period. At the firm level, two additional parameters parallel those at the sector level, characterizing the influence of coworker networks on the expectation of firm-level productivity and the firm-specific component of the transition cost, respectively.

We begin the model estimation by classifying establishments into "firm groups" based on their quality, as represented by their firm fixed effect quartiles as measured by the model in Abowd, Kramarz and Margolis (1999) (Henceforth AKM). The estimation process comprises three steps. Firstly, we calibrate the discount rate, the job-switching rate, the correlation of taste shocks for jobs within the same sector, and the firm-level adjustment costs. We also estimate parameters governing the production process for each sector and firm group using data on labor distribution and wages, along

[5]Following the existing literature, we introduce the idiosyncratic component to reflect randomness in job choice decisions. This component accounts for the fact that flows tend to be bilateral and not unilateral, and that a significant fraction (Bowlus and Neuman (2006)) of job switchers move to lower-wage positions.

with sectoral goods prices. Next, we estimate the job-switching wage elasticity and the two parameters characterizing firm-level influences of the coworker network, one capturing the influence of the coworker network on the average propensity to change firms and the other one characterizing the impact of the coworker network on the sensitivity of job-switching to firm-level wages. We combine two equations relating the size of within-sector, cross-firm flows to the fraction of job stayers at each firm. In a scenario without information friction or adjustment costs, the sum of bilateral flows with respect to the number of job stayers at each firm would be zero. On the other hand, with the existence of the coworker network, the sum of bilateral job flows depends on the inflows into one firm from the other, which allows us to identify the parameters related to how important coworker network is for firm-level TFP belief and cost of switching. With the strength of the firm-level coworker network known, the equation on unilateral flows helps identify the within-sector job switching elasticity and rate, after controlling for firm-level coworker composition. Finally, we estimate two parameters capturing sector-level influences from the coworker network, together with the sector-level transition cost that is sector-pair specific, by comparing the size of the cross-sector flows with the fraction of sector stayers. The moment conditions we use mirror our firm-level coworker network estimation method, examining bilateral flows across sectors and identifying the coworker network's impact through their asymmetry. Since estimating the sector-level coworker network requires knowing the value of being employed in any firm in a sector, we conduct this estimation step at the steady state, after solving for the model-implied inclusive values. We use Generalized Method of Moments (GMM) to jointly estimate all the sector-level parameters.

We aim to quantify the impact of coworker networks by comparing impulse responses of output, wages, and welfare during the transition to a new equilibrium, to the case without coworker networks. To achieve this, we use a quantified model to assess the impact of coworker networks on the adjustment toward new steady states in Germany following a shock akin to COVID-19, by leveraging the tractability of our model and combining it with micro-level data on wages and bilateral movements across firms and sectors.

While "labor mobility" is often viewed positively, it can have both favorable and unfavorable impacts on wages and welfare in a general equilibrium context. Although coworker networks can endogenously guide workers toward positively shocked sectors, the resulting increase in labor supply may suppress wages in those sectors, making the overall effect ambiguous ex-ante. Our findings show that labor reallocation into positively shocked sectors is both significant and long-lasting. Neglecting the coworker externality may lead to an underestimation of both the speed and the magnitude of labor transition. A decomposition of the welfare changes reveals that the general-equilibrium wage changes associated with shifts in labor allocation are the most important factor that leads to the discrepancies between the model with the coworker network and the one without, outweighing the partial-equilibrium effects of labor reallocation across sectors with varying productivity levels. Furthermore, the coworker model suggests that preserving worker-employer ties by slowing worker relocation to positively impacted sectors—thereby maintaining higher wages in those sectors through constrained labor supply adjustments—leads to higher average wages and welfare during the transition by mitigating the barriers to the positively shocked sectors, though it also contributes to increased wage inequality.[6]

The methodology underpinning these conclusions relies on the "Master Equation" approach. Coworker networks can be characterized by the labor flows across all firm groups in the economy, which is a high-dimensional set of variables. Keeping track of all flows in the data squares the dimensionality compared to other models, which typically only track labor distribution without accounting for labor flows. To circumvent the issue of including a high-dimensional object within the set of state variables, we leverage recent methodological advances from Bilal (2021), which utilize the "Master Equation" representation of the economy. By expressing labor flows as functions of the labor distribution, and taking first-order perturbations of the Master Equation in the underlying labor distribution and sectoral shocks around the initial deterministic steady state, we derive analytical Bellman equations for the directional derivatives of individual value functions with respect to the state variables and the aggregate shocks. The influence of the coworker network can be represented in a single matrix at the steady state. This approach allows us to obtain the impulse responses of the labor distribution, wage, and welfare with respect to an aggregate shock such as COVID-19.

This paper contributes to several distinct strands of literature. First, our work builds upon a rich tradition of research on the implications of sectoral shifts, labor mobility, and labor reallocation. Studies such as Lilien (1982), Abraham and Katz (1986), Brainard and Cutler (1993), and Shimer (2005) established the importance of sectoral reallocation for understanding unemployment and economic growth. In addition, works by Jovanovic and Moffitt (1990) and Neal (1995) explored factors enhancing sectoral labor mobility and highlighted the significance of sector-specific human capital in labor mobility decisions. More recent literature, including Dix-Carneiro (2014), Autor, Dorn and Hanson (2016), and Traiberman (2019), has investigated the impacts of trade shocks on labor market dynamics and sectoral reallocation.[7] Our paper extends this literature by explicitly incorporating the role of coworker networks into the process of sectoral reallocation. We demonstrate that these networks can significantly influence both the level and elasticity of sectoral transitions, providing a new perspective on the frictions that affect labor market adjustments.

This paper also adds to the growing literature on social networks in labor markets. Building on works by Rees (1966), Granovetter (1973), and Montgomery (1991), more recent studies such as Ioannides and Loury (2004), Calvo-Armengol and Jackson (2004), Topa (2001), Dustmann et al. (2016),

[6]Our conclusion is in line with the results in Beraja and Zorzi (2022), which shows that slowing down automation can be optimal for aggregate welfare to avoid depressing the earnings of workers whose jobs are being automated. Our results also emphasizes that worker reallocation is inherently costly and that the timing of the externalities of work movements matter for the effectiveness of policies.

[7]While not necessarily focused on the sectoral aspect, a vast existing literature has studied frictions that reduce job mobility in the labor market (Menzio and Shi 2011, Elsby and Michaels 2013, Acemoglu and Hawkins 2014, Bilal et al. 2022) and lead to misallocation of talents (Hsieh et al. 2019), and emphasize that worker reallocation can be costly (Mukoyama and Osotimehin 2019, Beraja and Zorzi 2022).

and Lindenlaub and Prummer (2021) have demonstrated the importance of social ties in job search and labor market outcomes. Glitz (2017) specifically examines the role of coworker networks, showing their impact on job mobility and wages. We extend this line of research by focusing on how one's network formed by current coworkers affects not just job changes within sectors, but also transitions across sectors. We provide new approaches, particularly the distinction between current-year and non-current-year coworkers and the use of coworker death and retirement events, for identifying causal effects of social networks in labor markets.

Finally, we speak to the literature on outside options and information frictions in the labor market. Outside options, by determining individuals' reservation wages and therefore their bargaining power, are a key ingredient in macroeconomic search and matching models (Pissarides 2000, Postel-Vinay and Robin 2002, Moscarini 2005, Cahuc, Postel-Vinay and Robin 2006, Bagger et al. 2014, Jarosch 2023).[8] Moreover, it is not solely the outside options alone that matter, but also workers' beliefs about these options that influence their labor market decisions and outcomes (Stigler 1962, Conlon et al. 2018, Caldwell and Harmon 2019, Porcher 2020, Jäger et al. 2024, Bradley and Mann 2024). We also show that coworkers, by influencing one's beliefs on productivity in other sectors, can influence her perceived outside options. Our paper differs from the prior literature in its focus on the influence of the belief of outside options on workers' mobility decisions across sectors.

Our paper makes several key contributions. First, building upon work emphasizing the role of social networks in influencing job choice, we establish a positive causal relationship between the past sectoral composition of an employee's current coworkers and the sector of her future job. Second, methodologically, we build the coworker channel explicitly into dynamic discrete choice models that study labor reallocation following shocks. Importantly, we do this in a succinct way by summarizing the influences of coworker networks through four parameters, allowing the model to be easily adaptable to other settings. Third, we provide a method to compute the impulse response functions of the model and study its counterfactuals through local perturbation around the steady state. Finally, we quantify the impact of coworker networks on policies that restrict or redirect labor movements across sectors by comparing aggregate responses and distributions to the model where all coworker-related parameters are set to zero.

The rest of the paper proceeds as follows. Section 2 discusses the positive correlation between an individual's share of coworkers from a particular sector and their propensity to transition into that sector due to idiosyncratic reasons. Section 3 develops a tractable model in which workers' job and sector choices are influenced by their coworkers. Section 4 details our identification strategy and presents estimation results. Section 5 evaluates the effectiveness of policies that maintain worker-employer ties, such as short-term work arrangements. Section 6 concludes.

[8]The minimum wage, by setting a wage floor, can also effectively alter workers' outside options and influence their job search behavior and bargaining power. Studies such as Manning (2013) and Engbom and Moser (2022) have analyzed the implications of minimum wage policies in labor markets, demonstrating how they can improve workers' outside options and potentially increase employment. Aaronson et al. (2018) examined how minimum wage hikes affect firm dynamics and labor reallocation, highlighting the role of outside options in shaping employment responses.

2 Reduced-Form Evidence

We begin our analysis using linked employer-employee data from Germany to explore the causal relationship between the sectoral backgrounds of coworkers and individuals' decisions to switch jobs. Specifically, we aim to determine whether the sectors from which coworkers have recently transitioned influence an individual's likelihood of moving to those same sectors, and how sensitive this decision is to wage differences. Importantly, we assess these effects while controlling for factors like sector-specific productivity shocks and the inherent, time-varying difficulty of transitioning between industry pairs. To achieve this, we analyze how the composition of a worker's current coworkers' previous employment sectors affects their likelihood of switching to particular industries.

Our reduced-form analysis uses the German social security data that contains the full employment history of the complete set of employees at establishments randomly sampled in the German economy from 1975 to 2018. The data is from the Integrated Employment Biographies (IEB) database of the Institute for Employment Research (IAB). The data set is in employment spell formats. Establishments report to social security agencies for various reasons, including annual notifications, employment interruptions, terminations, and employee deaths. It includes information on the start and end time of each job, for all workers that are employed in the sampled establishment in the middle of each year. Additionally, it includes worker characteristics, including age, gender, nationality, skill and training levels, tenure, wage up to the censoring limit, federal state and district of the workplace, occupation, etc.

For our empirical analysis, we turn this dataset into yearly cross-sections by finding all workers who has ever been employed in a certain establishment in a given year and identify all job switchers in a given year. There has been a sizeable existing literature that uses similar data source (Card, Heining and Kline 2013, Dustmann et al. 2014, Brinatti and Morales 2021, Jäger and Heining 2022, Freund 2022).[9] We follow this literature by using the terms "firms" and "establishments" interchangeably. Appendix A.1 describes the process for constructing the data set and presents summary statistics on establishments and job switchers. Summary statistics for our individual-level evidence could be found in Appendix A.4.

2.1 Individual-Level Evidence

We start with the baseline specification implemented on the sample of all job switchers who move into jobs different from their current sectors:

$$\begin{aligned}\mathbb{1}_{pijt} =& \alpha_0 + \alpha_1(\ln \hat{w}_{pjt} - \ln w_{pit}) + \alpha_2 \tilde{\theta}_{pjt} \times (\ln \hat{w}_{pjt} - \ln w_{pit}) + \\ & \beta_1 \tilde{\theta}_{pjt} + \beta_2 \frac{1}{T-1} \sum_{k \neq t} \theta_{pjk} + \zeta_{io(p,t)jt} + \xi_{l(p,t)t} + \Gamma X_{pijt} + \varepsilon_{pijt}\end{aligned} \tag{1}$$

[9] Some of the existing works mentioned use an alternative lined employer-employee dataset from the FDZ, Linked-Employer-Employee-Data of the IAB (LIAB).

where $\mathbb{1}_{pijt}$ is equal to 1 if individual p originally employed in industry i switches to industry j in year t. $\hat{w}_{pjt}$ is the predicted wage that the individual would have earned had she moved to destination sector j. $o(p,t)$ and $l(p,t)$ represent the occupation and location of work for individual p in year t. w_{pit} is worker p's current wage while working at establishment p. $\tilde{\theta}_{pjt} = \theta_{pjt} - \frac{1}{T-1}\sum_{k\neq t}\theta_{ejk}$ is the difference between the share of p's current-year and non-current year coworkers who were employed in industry j for their last jobs; it nets out the time-invariant transition difficulty between the origin firm and the destination sector, and will be discussed in more details. Our coefficients of interest, denoted as α_1 and α_2, gauge how the propensity to move across sectors, as well as the change in this propensity with respect to the potential wage differential, change relative to an individual's share of coworkers last employed in those sectors before starting their current employment. We also include the main effect of the difference between the current-year and non-current-year coworker shares that encapsulates the easiness of moving between the origin establishment and the destination sector that may impact decisions to move during the current calendar year.

The current-year coworker share may capture other factors that affect labor transition from a certain establishment to the destination industry that can lead to an increase in the firm's employees' likelihood of transitioning to the destination industry but are unrelated to the share of coworkers coming from that industry. To address this issue, we control for a variety of other variables that may influence individuals' sectoral choice decisions and may be correlated with the coworker composition in their current establishment in the regression. $\zeta_{io(p,t)jt}$ represents a collection of industry-pair-specific, occupation-specific, and year-specific fixed effects. These fixed effects help account for various time-varying shocks that separately affect certain occupations either within the origin or within the destination industries, as well as any evolving barriers to transitioning between these two industries. By introducing controls that consider the occupational dimension, we accommodate variations in the ease of transitioning between certain sectors based on an individual's occupation.[10]

Other than controlling for the time-varying shocks specific to each industry pair and occupation, we control for other variables that may also influence inflows to and outflows from a sector. $\xi_{l(p,t)t}$ is a set of location-by-year fixed effects. Under the assumption that labor is being supplied to the local labor market inelastically, the location-by-time fixed effects tease out the factors on the labor-supply side that are correlated with individuals' sectoral choices and consequently the potential wage differential the individuals face when switching to a certain destination industry. The set of individual-level control variables X_{pijt} includes the nationality (German vs. foreign), gender, full-time status, skill level, vocational training level, age quintile, tenure quintile, and days of unemployment of the worker in current calendar year. This is the set of controls included in all individual-level regressions, unless otherwise stated.[11] The error term ε_{pijt} captures unobservable factors that drive job switchers' indus-

[10]For instance, jobs like human resource managers might be recruiting across a wide range of industries, while others like healthcare professionals are typically associated with specific fields due to the specialized nature of their skills.

[11]Skill levels are classified into four categories: unskilled/semiskilled task, skilled tasks, complex tasks, and high complex tasks. Vocational levels are classified into six categories: secondary/ intermediate school leaving certificate without completed vocational training, secondary/ intermediate school leaving certificate with completed vocational training, up-

try choice, i.e. amenities in the destination industries, as well as workers' idiosyncratic preferences or their expectational errors on the wages that they could have received after switching jobs. The specification is implemented on all job switchers, by pooling across all destination industries.[12] The analysis is at the sector level.

Regression specification (1) highlights the significance of coworker inflows in influencing workers' sector-switching decisions, beyond merely capturing the productivity of level of these sector and the inherent transition difficulty across sectors. However, a confounding factor arises from the possibility that certain establishments exhibit lower barriers to transitioning into specific destination industries. This scenario could lead to an increase not only in the current-year coworker share θ_{pjt} but also in the propensity to switch $\mathbb{1}_{pijt}$. Furthermore, as the fixed effects in our baseline regression are at the sector level, they do not account for this establishment-specific transition difficulty. Consequently, if we solely include the current-year coworker share in the regression, this confounding factor may bias the coefficient estimates upwards.

Our solution to this issue is to differentiate between *current-year* coworkers and *non-current-year coworkers*. While the non-current-year coworker share encapsulates the overall difficulty of transitioning between the establishment and the industry of interest across all years, the current-year coworker share encompasses both the general challenges associated with job transitions and the plausibly exogenous changes in coworker composition specific to the given year. The identifying variations in our approach stem from recent employee arrivals and departures from their current establishments.[13] Our baseline empirical approach relies on the identifying assumption that no other variables will concurrently influence both an individual's sectoral choices and the composition of their coworkers' prior sectors of employment. This assumption is likely to hold, given our inclusion of a comprehensive list of industry-level fixed effects in the regression and our control for non-current-year coworker shares from each origin industry of interest.

Our analysis is focused on investigating how the coworker network influences workers' responsiveness to wage increases when transitioning between jobs in distinct sectors. An inherent challenge arises from our inability to directly observe the wage an individual would have attained if they had opted for a different sector. It is imperative to find a proper proxy for this unobserved wage to calculate the wage differential that the job seeker would have incurred by moving into another sector in a way that reduces attenuation bias. Our idea is to match each job switcher and her origin firm to other worker-firm pairs that are comparable, and in which the worker chose to switch to the destination

per secondary school leaving certificate without complete vocational training, upper secondary school leaving certificate with complete vocational training, completion of a university of applied sciences, college/ university degree.

[12]More specifically, a single job switcher p appears in the data N times in year t, where N is the number of industries according to the level of industry classification. $\mathbb{1}_{pijt}$ if equal to 1 if the individual switches into j, and is equal to 0 otherwise.

[13]This methodology can be perceived as conservative in approximating the informational influence propagated by coworkers. This is because employees with longer tenures in an establishment, while representing labor demand similarities between the firm and the target sector, may also be able to influence workers' transition to their previous sectors by bringing along information about such sectors or reducing the adjustment costs of moving into those sectors. For example, coworkers may reduce the adjustment costs of transitioning into their previous sectors by helping their colleagues to develop relevant skills or by introducing them to others that are still employed at that sector.

sector of interest. We employ three methods to impute the potential wage. First, we calculate the wage averaged across all individuals in the same state, sector and occupation within a given year for the reference worker. Second, we calculate the average across all workers while additionally accounting for the firm and worker quality as represented by the AKM firm and person fixed effects. Third, we use the average wage of an individual's current colleagues who used to work in the destination sector of interest as a proxy. Given that AKM fixed effects and coworkers previously employed in an industry are both observed only for a subset of workers, we use the first method as our preferred specification. A more detailed description could be found in Appendix A.2.

2.2 Baseline effect estimates

We implement the specification using various definitions of coworkers. First, we define coworkers as individuals working in the same establishment and occupation, as communication among employees within similar occupations tends to be more frequent and valuable. Second, considering potential variations in interaction dynamics influenced by peer attributes from their prior employments, it's plausible that higher-earning individuals might exhibit a greater inclination to divulge insights about their past positions or enjoy a higher capability of sharing their skills to their current coworkers, unlike their lower-earning counterparts. We classify coworkers based on whether their industry-occupation-specific wages are above or below the average and subsequently incorporate into the regression analysis only those individuals whose wages fall below this average threshold. Third, our baseline analysis constructs the non-current year coworker variable ($\frac{1}{T-1}\sum_{k\neq t}\theta_{pjk}$) in specification (1) using all years available in the data. However, one may worry that since the dataset spans multiple years, the years further away from t do not effectively capture the labor demand similarity between the establishment and the destination sector during t and that the transition difficulty specific to a firm and sector pair may not remain constant over a long time period. We address this concern by constructing the non-current-year coworker share using only one year prior to and one year after the reference year. Lastly, we introduce an additional control representing the share of past coworkers currently employed in the destination firms of job switchers.[14]

The results for the baseline specifications using various coworker definitions are reported in Columns (2) - (5) of Table 1. Standard errors in all specifications are clustered at the origin establishment level to account for correlated sectoral choices among individuals working within the same

[14]The existing literature extensively documents how personal connections, particularly relationships with coworkers, can enhance job-to-job mobility and wage growth (Glitz 2017; Caldwell and Harmon 2019, Saygin, Weber and Weynandt 2021). This body of research emphasizes the role of social networks in facilitating information transmission, which positively impacts individuals newly entering the labor market and those already employed. Specifically, it focuses on the variation in the share of former coworkers at firms individuals can transition into, highlighting how awareness of outside options or direct referrals to destination firms can be influenced by coworker networks. Our research diverges from this line of research in two key aspects. Firstly, instead of exploring whether former coworkers direct individuals to their current positions, we leverage the *former places of employment of the current coworkers* as the source of variation in our coworker network measure. Secondly, our project delves into the sector-choice dimension. Rather than solely emphasizing the role of networks in directing individuals to better, more productive options, we investigate how mobility itself generates positive externalities, even for workers transitioning from more to less productive sectors, thus accelerating sectoral reallocation.

firm, which are not explained by sector-level fixed effects.[15]

Table 1: Impact of Coworkers on Sector-Switching

	(1)	(2)	(3)	(4)	(5)
Coworker	0.121***	0.108***	0.105***	0.125***	0.116***
	(0.0009)	(0.0006)	(0.0013)	(0.0009)	(0.0009)
ln(Wage Diff)	0.005***	0.004***	0.006***	0.004***	0.005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Coworker × ln(Wage Diff)	0.033***	0.041***	0.038***	0.028***	0.041***
	(0.0010)	(0.0008)	(0.0014)	(0.0010)	(0.0009)
Occupational-specific coworkers		✓			
Coworkers with lower wage			✓		
Controls for coworker connection				✓	
Recent-year coworker					✓
Mean of Dep. Var	0.07	0.07	0.07	0.07	0.07
R^2	0.31	0.32	0.31	0.32	0.31
Observations	151,241,259	151,241,259	151,241,259	151,159,037	151,241,259

Notes: Table displays $\hat{\alpha}_1$, $\hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for specification (1). Standard errors are clustered at the origin establishment level. The dependent variable in all regressions is the probability of switching to a certain destination sector. Second column estimates potential wage at a destination sector for an individual at an origin establishment by averaging across the wages of all those who share the same person and firm FEs quantiles from an AKM regression and are employed in the destination sector. Third column estimates potential wage at a destination sector by averaging across all past wages of coworkers at the current firm who just transitioned from the sector. Fourth column defines coworker shares at the establishment × occupation level. Fifth column includes as coworkers only those with below-average wage at their previous job. Sixth column excludes as coworkers those who are employed in the same destination establishment. Seventh column defines non-current-year coworkers using only one year prior and one year after the reference year.

Our findings highlight statistically significant impacts of coworker information on both the propensity to transition into a specific sector and the sensitivity of this propensity to changes in wages. In column (1), adjusting the coworker shares from a particular sector that just arrived from 0 to 1 in the current-year relative to the non-current-year, and keeping other covariates constant, individuals are, on average, 12.1 percentage points more likely to move to that sector. Moreover, the influence of current coworkers' past sectoral composition on the likelihood of moving also amplifies with relative wage differences. A 50% wage increase corresponds to an additional 1.3 percentage points likelihood of moving to that sector when adjusting the difference between current-year and non-current-year coworkers from that sector. Noteworthy is that the estimate $\hat{\alpha}_2$ surpasses the estimate for the main effect of sectoral move probability on wage differentials, $\hat{\beta}_1$, by more than six times. This suggests that variations in the coworker network can substantially enhance individuals' responsiveness to wage changes.[16] The magnitudes remain consistent when employing alternative imputation methods for

[15] We check that our conclusion is robust to alternative approach of clustering standard errors. In particular, we run an otherwise identical regression with standard errors clustered at the destination sector level, to address the concern that the outcome variables are negatively correlated for each individual. The standard errors and conclusion remain comparable.

[16] Admittedly, our imputations for wage differentials may introduce some measurement errors that are unrelated to the key independent variables of interests, which may attenuate the coefficient estimate for $\hat{\beta}_1$ toward zero. However, given that the imputed destination-sector wage distribution does not excessively compress the actual distribution, it could be reasonable to conjecture that the magnitude of $\hat{\alpha}_2$ remains considerable compared to the true propensity to move across

destination-sector wages. As seen in Table B2, imputing $\hat{w}_{pjt}$ through the averaging of those with the same firm- and person-fixed effects from an AKM regression yields higher estimates for both $\hat{\beta}_1$ and $\hat{\alpha}_2$. This could result from that this wage measurement method does not compress the wage distribution as much as the baseline, indicating greater accuracy. Conversely, utilizing coworker wages leads to a slight decrease in the estimates for both $\hat{\beta}_1$ and $\hat{\alpha}_2$. This may be attributed to the wages of coworkers who recently left a specific industry representing an underestimation of the wages individuals would have earned upon moving to that industry.

The influence of coworkers on sectoral choices may vary depending on their personal characteristics. To explore these outcomes, we examine alternative coworker definitions. Comparing column (1) with columns (2), (3), and (5) of Table 1, the results indicate that the increase in the average propensity to move to a specific destination sector due to variation in coworkers' last sector of employment does not significantly depend on occupation, previous wage, or the timing of job changes among these coworkers. However, having more coworkers from the same occupation or those who have recently transitioned from their prior job in a sector increases the elasticity of moving to that sector with respect to potential wage gains. These findings support the notion that more intensive and beneficial interactions occur with individuals in the same occupation who have recently changed jobs.

Additionally, controlling for the shares of coworkers employed at the destination establishment does not significantly alter the magnitude of the main effect and only slightly decreases the estimate of the influence of coworkers on workers' moving elasticity with respect to wage differentials. This provides evidence against the conjecture that the results are primarily driven by workers following their past colleagues to their current firms unidirectionally due to factors such as referral opportunities.

Heterogeneity In addition to the baseline analysis that pools across all job-switchers, we examine the heterogeneity of the effects by running regression specification (1) separately for workers of different gender, nationality, as well as quintiles of the age, and tenure distribution, to compare the effect size for workers with different characteristics. This analysis shows that the influence of coworkers prevails across the entire labor market. Appendix B.3.1 discusses the results on worker heterogeneity in more details.

Robustness We include a number of tests for robustness. First, to test whether including the interaction between the difference in the current-year coworker share and non-current-year coworker share and the wage differential suffices for characterizing the importance of the coworker network on move elasticity, we examine a specification where we control for additionally $\frac{1}{T-1}\sum_{k\neq T}\theta_{pjk} \times (\ln \hat{w}_{pjt} - \ln w_{pjt})$. Besides, to address the concern that non-current-year coworker shares may capture future shocks on top of past shocks, we study the specification where we replace the non-current-year coworker shares are replaced by the one-year-lagged coworker share, to capture the most recent realized transition difficulty at the origin firm $\times$ destination industry level. The results are shown in

sectors in response to wage differences.

Table B3.

Note that in our baseline specification (1), we include a variety of control variables, including individual-level characteristics, the full set of fixed effects by interacting the origin and destination industry, occupation, and year, as well as the location-by-year fixed effects. In Table B4, we test how each component of this rich group of control variables influences the coefficient regression estimates of interests by adding in subsets of the controls gradually into the regression specification. The coefficient estimate $\hat{\alpha}_2$ remains statistically significant and stable in magnitude across all specifications.

Apart from testing the significance of the control variables, we assess in alternative samples the robustness of the correlation between the past sectoral composition of individuals' coworkers and their responsiveness to potential wage differentials to alleviate concerns about other factors driving the results. First, we exclude job switchers who also switch states. Second, we exclude workers with top-coded wages in the data. Third, we exclude all pairs of origin establishment and destination sector with zero-valued flows. Fourth, we exclude the cases where workers transition back to their past sector of employment before the onset of their current job. Fifth, we classify industries more finely and conduct the analysis at establishment, as opposed to the individual level. The relationship between coworkers and sectoral-switching remains prevalent across all samples. A more detailed description on each robustness could be found in Appendix B.3.2 and B.3.4.

2.3 Evidence from Coworker Death and Retirement

In addition to the baseline coworker analysis, we incorporate a quasi-experimental design that leverages worker deaths and retirements as a source of variation in individuals' coworker composition to address endogeneity concerns. In smaller establishments, the exogenous deaths and retirements of employees can significantly alter the coworker composition, leading to an immediate reduction in the share of coworkers coming from the sector where the deceased or retired worker was last employed. If coworker networks indeed affect one's sector choice decisions beyond merely characterizing transition difficulty, this would manifest in different transition behaviors of incumbent workers before versus after the coworker death, as well as differential switching patterns between incumbents and new hires with otherwise comparable characteristics.

Therefore, our approach is to employ coworker deaths and retirements as an instrumental variable for the share of coworkers in each establishment previously coming from a certain sector. We compare the sectoral choices of both incumbent workers and new hires from an establishment that underwent a coworker death or retirement with those of other employees transitioning out of a similar establishment that did not experience a worker death or retirement. We identify deaths in the dataset using the "reason for notification" variable and limit our analysis to deaths of workers with a preceding unemployment duration of no more than six weeks. Given the absence of a category explicitly indicating retirement in the "reason for notification" variable, we identify exogenous retirement events by locating all workers with no subsequent job after reaching retirement age and selecting individuals whose reasons for notification indicate deregistration from the system and an end to their employment.

To ensure that the death and retirement events serve as a sharp shock to the firms' coworker composition, we follow Jäger and Heining (2022) and exclude notifications after which we still observe spells for the individual after more than 30 days, or those in which the worker began decreasing her time, either by working part-time or taking days off, long before passing away or retire. Additionally, we exclude cases where the deceased or retired worker's last establishment of employment belongs to the same sector or the job, as such workers may not bring any additional information or additional skills to their workplace. Further details on identifying death and retirement events in the data can be found in Appendix A.1.

We assign treatment status to the deceased worker-establishment pairs that match our criteria and find other worker-establishment pairs with similar characteristics but without experiencing an actual death or retirement by matching on their characteristics. Specifically, denote the year of death or retirement by t and the year relative to the death or retirement event by s, we match exactly on a large set of characteristics for each worker employed in a firm where a worker originally from industry j before coming to work at this current firm passes away or retires among the set of non-deceased, non-retired worker-establishment pair in year t.

At the worker level, we match on the following characteristics: nationality (Germany vs. foreign), gender (Female vs. Male), skill level (skilled vs. non-skilled), education level (secondary/intermediate school vs. upper secondary school vs. college), full-time status (full-time vs. part-time), age (quartile), wage(quartile), tenure (quartile), last sector of employment, time since switching to the current job (more than vs. less than one year) at time d. At the establishment level, we match on size (quintile), AKM firm fixed effect (quartile), share of workers in industry j (above vs. below 50%) at time d. More details on the matching method could be found in Appendix A.3. Appendix A.5 presents the summary statistics for our death analysis sample. Individuals in the treatment and control groups are comparable in terms of personal attributes, tenure, and wages. At the establishment level, those with actual deaths or retirements are slightly larger than those in the control groups and have somewhat fewer new hires and job switchers. However, establishment quality, as measured by AKM firm fixed effects, is commensurate across treatment and control groups.

Assuming that treatment status is uncorrelated with other establishment-level or individual-level characteristics and thus exogenous to other workers' job-switching decisions, we instrument the coworker share from the deceased or retired person's industry in an establishment using three factors: the year relative to the event, the treatment status of the establishment, and their baseline coworker share.[17] The first stage is:

$$\theta_{ejt} = \alpha_0^{first} + \sum_{s=-3}^{3} \alpha_s \times \mathbb{1}_{t=d+s} + \sum_{s=-3}^{3} \alpha_s^{Treated} \times \mathbb{1}_{t=d+s} \times \text{Treated}_{pe} + \gamma_0^{frist} \frac{1}{T} \sum_k \theta_{ejk} + \zeta_{io(p,t)jt} + \epsilon_{ejt} \tag{2}$$

where e denotes establishment. d and s represents respectively the year of death or retirement event, and the year relative to that event. $\mathbb{1}_{t=d}$ therefore an indicator for the calendar year being s years relative to death or retirement within the establishment. We include the mean of the coworker share across all years used for the analysis, $\frac{1}{T}\sum_k \theta_{ejk}$, to control for the baseline coworker share within an establishment as well as its average effect on the propensity of workers within that establishment to move to the destination sector of interest.

Apart from the share of coworkers, in equation (3), we instrument for the interaction term of coworker share from industry j and the wage differential between the destination industry wage and the individual p's current wage, since this term also involves the endogenous variable. We achieve this by specifying a first-stage regression equation incorporating years relative to death or retirement, treatment status of the establishment, the non-current-year coworker shares, and their interactions with the wage difference.

$$\begin{aligned}(\text{Share} \times \text{Wage})_{peijt} = \alpha_0^{first'} &+ \sum_{s=-3}^{3} \alpha'_s \times \mathbb{1}_{t=d+s} + \sum_{t=-3}^{3} \alpha_s^{Treated'} \times \mathbb{1}_{t=d+s} \times \text{Treated}_{pe} + \\ &\sum_{s=-3}^{3} \beta'_s \times \mathbb{1}_{t=d+s} \times (\ln \hat{w}_{pjt} - \ln w_{pit}) + \\ &\sum_{t=-3}^{3} \beta_s^{Treated'} \times \mathbb{1}_{t=d+s} \times \text{Treated}_{pe} \times (\ln \hat{w}_{pjt} - \ln w_{pit}) + \\ &\gamma_0^{first'} \frac{1}{T-1} \sum_{k \neq t} \theta_{ejk} + \gamma_1^{first'} \frac{1}{T-1} \sum_{k \neq t} \theta_{ejk} \times (\ln \hat{w}_{pjt} - \ln w_{pit}) + \zeta_{io(p,t)jt} + \epsilon'_{pejt}\end{aligned} \tag{3}$$

The destination-sector wages are approximated as the average of the wages for all workers working in the same sector at a given year, same as the baseline. With the instrumented variables, we then estimate the second stage:

$$\mathbb{1}_{pijt} = \alpha_0 + \alpha_1(\ln \hat{w}_{pjt} - \ln w_{pit}) + \alpha_2 (\widehat{\text{Share} \times \text{Wage}})_{pijt} + \beta_1 \hat{\theta}_{pjt} + \zeta_{io(p,t)jt} + \varepsilon_{pijt} \tag{4}$$

where $\hat{\theta}_{pjt}$ and $(\widehat{\text{Share} \times \text{Wage}})_{pijt}$ are the predicted coworker shares within individuals p's establishment, and the predicted value of the interaction between this share and the wage differential she

[17] We include the average coworker share in the first stage as it likely correlates with an individual's coworker share. Moreover, since we control for non-overlapping coworker shares and include a set of fixed effects at an even more granular level, it is unlikely to correlate with individuals' switching decisions through channels not already accounted for.

would have faced going into sector j.[18] Each individual is weighted by the inverse of the total number of incumbent workers at an establishment, ensuring that all worker deaths and retirements have equal weight.[19] As in the baseline model, we include a set of fixed effects at the industry pair-by-occupation-by-year level.[20]

The number of instruments exceed that of the endogenous variables, and we use GMM to calculate the optimal weighting matrix. Same as in the baseline, p and e index individuals and the establishments in which the individuals are employed, i and j denote the origin and the destination industries, and t indexes calendar year. $\mathbb{1}_{pijt}$ is the indicator for individual p in sector i switching into sector j during calendar year t. $\tilde{\theta}_{pet}$ is the share of coworkers for individual p in establishment e that switch to sector where the deceased or retired worker of this establishment was previously employed before her employment started. $\frac{1}{T-1}\sum_{k\neq t}\theta_{pek}$ is the non-current-year coworker share from the deceased or retired person's industry in establishment e. We additionally represent by d the year of the actual or placebo death or retirement event, and by s the year relative to that event. $\mathbb{1}_{t=d+s}$ is therefore an indicator for being s years away from the death or retirement of coworker within one's establishment. Treated_{pe} is an indicator for establishment e being in the treatment group.

The results of our IV analysis are shown in Table 2. Column (1) includes all workers in either the treatment or the control group. Column (2) uses only establishments with death events (excluding retirements). Column (3) focuses on the impact on new hires that just joined a certain establishment and studies whether they will change jobs within the current year. Since we now include all individuals in the sample, including non-job-switchers, the coefficient estimates for coworker shares in influencing the average propensity to switch sectors become approximately 40% of the baseline when we include both establishments with death and retirement, and around 20% of the baseline when we include only establishments with death. Nevertheless, the coefficient estimate remains positive and significant, ruling out the concern that coworker networks may influence decisions only conditional on choosing to switch jobs in the first place. Additionally, the elasticity of moving decisions with respect to the potential wage differential increases slightly compared to the baseline, suggesting the possibility that coworkers may influence the extensive margin of job switching with respect to wage.[22] Finally, new hires are found to be more likely to switch sectors compared to incumbent work-

[18] We omit the subscript e that denotes the individuals' establishment of employment in equation (4).

[19] Specifically, one establishment in the control group may be matched to multiple establishments in the treatment group if its values of coarsened variables correspond to more than one observation in the treatment group and its propensity score is the highest among all candidate establishments sharing the same values of the coarsened variables. In such cases, we weight the placebo establishment based on the number of treatment firms it is matched to.

[20] We define the origin industry, i, more finely, using the three-digit NACE code classification.[21] Our rationale for this finer control is to better account for time-invariant establishment-level unobservables that may affect either the coworker share or individuals' propensity to switch sectors through channels other than the average coworker shares. Since our first stage aims to proxy for the change in coworker shares resulting from changes relative to the death or retirement event, we seek to control for as many persistent establishment characteristics as possible, to allow the average probability to experience a death or retirement event to vary by establishment characteristics across the treatment and the control groups. While it can be argued that death is random across establishments, retirement events may be more likely to be affected by other factors, especially those specific to each industry group given, for example, changes in industry-specific shocks that pose a health hazard to all workers employed in those industries.

[22] As the potential wage gain becomes larger, having more coworkers may lead a worker who would have been a stayer

ers. Their average propensity to do so and their responsiveness to wage differences are also more heavily influenced by the composition of coworkers at their current jobs. Since incumbent workers may be capable of continuously enjoying the benefits from the skills or information acquired from their previous coworkers at their current job before their death or retirement, the death or retirement events are not as sharp a shock as they could be for the new hires that have no previous interaction with others from the reference establishment. In Appendix B.3, we include a robustness check where we control for the industry-pair-by-occupation-by-year fixed effects, one in which both the destination industry and the occupation are defined at the 3-digit level. While the magnitude of the main effect decreases by around 30% compared to in Table 2, all coefficient estimates remain positive and statistically significant. This specification shows that the coworker mechanism remains valid after controlling for time-varying labor demand shocks for different skills required by a certain industry pair to the best extent possible.

Identification Assumptions The identification assumption at the core of our death and retirement analysis posits that the year relative to the death or retirement event is correlated with the coworker share from a certain origin sector. Given that death or retirement mechanically alters an establishment's coworker composition conditional on the establishment not immediately hiring a new employee to replace the deceased or retired worker, this condition is likely to hold. Nevertheless, we explicitly check for the relevance of the instrument in our first-stage analysis, by comparing the share of coworkers before vs. after deaths or retirements. We examine the relevance of our instruments using the following equation:

$$share_{ejt} = \sum_{s=-3}^{3} \alpha_s \times \mathbb{1}_{t=d+s} + \sum_{s=-3}^{3} \alpha_s^{Treated} \times \mathbb{1}_{t=d+s} \times \text{Treated}_e + \zeta_{ej} + \gamma_d + \gamma_t + \epsilon_{ejt} \quad (5)$$

Figure 1 demonstrates that firms in the treatment group initially have a similar share of workers from the deceased or retired individual's previous sector as the control group. However, in the first year after the death or retirement event, this share decreases by 5% in the treatment group. Even three years post-event, the treatment group maintains a 4% lower share of employees from the affected sector compared to the control group. These findings address concerns about the relevance of our death or retirement instrument for coworker shares. They show that firms do not immediately replace the departed worker with someone from the same sector, which could have potentially negated the instrument's relevance.

Moreover, the exclusion restriction requires that the occurrence of worker death or retirements within an establishment affects workers' transition decisions only by shifting the coworker shares, and does not exert additional influence on other employees' decisions to transition across sectors once we account for the relevant covariates. Potential threats to identification would be the existence

to become a switcher to the sector where they could enjoy this wage gain.

of contemporaneous shocks that change the possibility of death or retirement within each firm and also affects individuals' sectoral choices. Since we observe establishments before the actual or placebo death or retirement, we can also assess whether this condition is likely to hold by looking at pre-periods for the first stage of the IV analysis, regressing the share of coworkers last employed in the sector which the deceased or retired employer transitioned from.

Beyond the potential correlation in timing with other shocks affecting sectoral choices, another threat to identification arises from the direct influence a deceased or retired coworker may have on one's sectoral choice decisions. This influence could manifest through decreased workplace morale or productivity, or by triggering workplace restructuring that extends beyond altering coworker composition, potentially impacting incumbent workers' likelihood of transitioning to other jobs.[23] To address this concern, we implement an additional test to assess whether workers are generally less likely to switch jobs following a coworker's death or retirement. This test involves evaluating the following regression in the sample of treatment establishments:

$$\mathbb{1}(\text{Switch Job})_{pet} = \sum_{s=-3}^{3} \alpha_s \times \mathbb{1}_{t=d+s} + \zeta_e + \gamma_t + \epsilon_{pet} \tag{6}$$

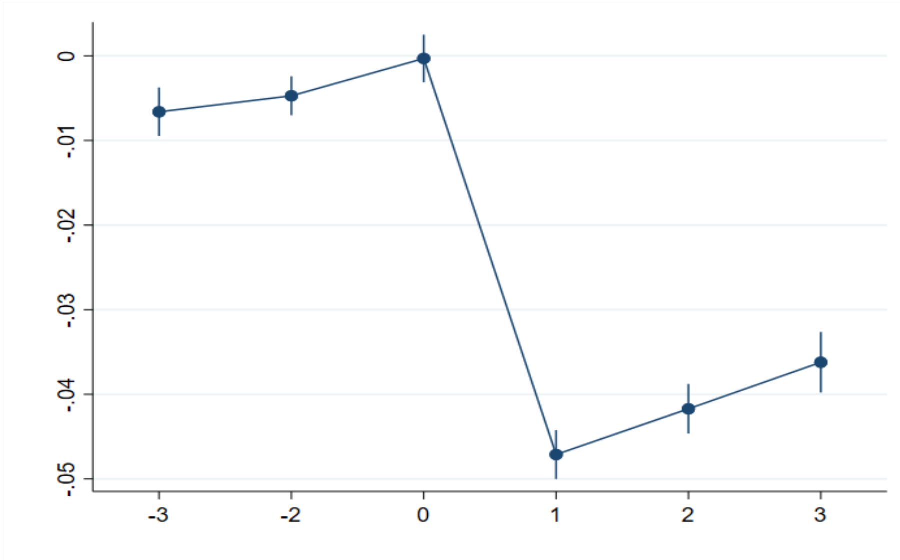
As illustrated in Figure 2, individuals exhibit a higher likelihood of switching jobs following the death or retirement of a coworker. This observation mitigates concerns that such events might directly reduce job-switching propensity beyond their impact on the changing composition of coworker shares within the establishment.

2.4 Job Quality

After establishing the causal link between one's coworker networks and her sectoral choice decision, another key question arises: can one's coworker network facilitate transitions not only into a new industry but specifically into higher-quality firms within that industry? Beyond simply providing general information about sectoral opportunities, coworkers may possess unique insights about firm-level conditions, such as productivity, workplace culture, or growth potential, that vary widely within industries. If coworkers share knowledge about this distribution of firm quality or if they impart skills that ease adaptation to more demanding, higher-quality firms, we might expect that individuals with more coworkers from a given industry would not only enter that industry more readily but would also be drawn to its top-performing firms. Such a network effect would suggest that coworker connections do more than assist in sectoral transitions—they actively shape the quality of opportunities available within sectors, steering workers toward positions that offer greater productivity and poten-

[23] For instance, studies on internal labor markets (Doeringer and Piore 2020, Baker, Gibbs and Holmstrom 1994) suggest that deaths and retirements could affect labor markets internal to each establishment, resulting in promotions for incumbent workers. This, in turn, may reduce their willingness to seek opportunities outside the current firm. This dynamic is particularly relevant to our IV analysis, which includes all workers and not just the job switchers. If workers become less likely to switch jobs overall due to internal labor market effects, it could confound the relationship between the decline in sector-switching propensity and the observed changes in coworker composition.

Figure 1: Impact of Death and Retirement on Coworker Composition



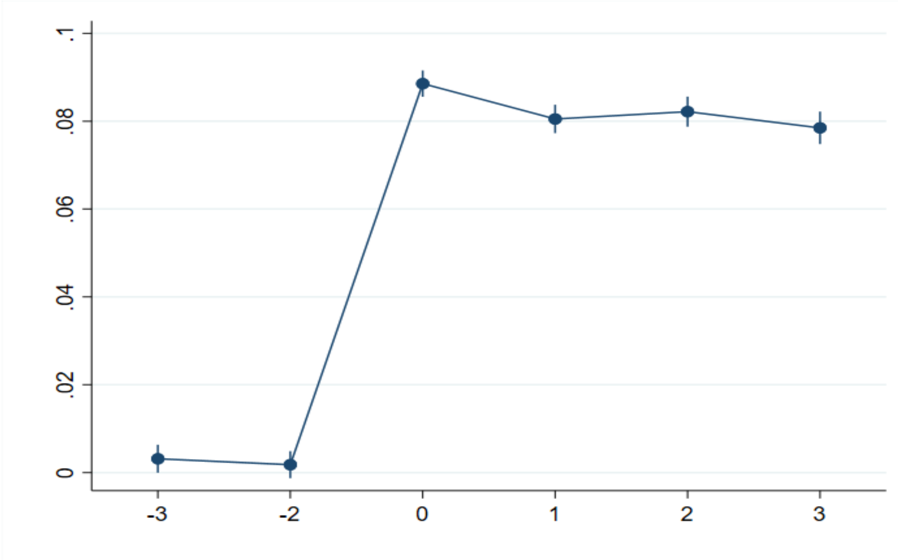
Note: Data source: SIEED. Figure plots, for establishment that experience a death or a retirement event, the share of coworker last employed in the deceased or the retired person's previous sector of employment against the years relative time at which the death or retirement event takes place. In particular, these correspond to the $\alpha_s^{Treated}$ estimates in equation (5).

Table 2: Estimation Results for Specification (4)

	(1)	(2)	(3)
Coworker	0.049***	0.021**	0.137***
	(0.0047)	(0.0106)	(0.0122)
ln(Wage Diff)	0.011***	0.009***	0.005
	(0.0013)	(0.0029)	(0.0035)
Coworker × ln(Wage Diff)	0.044***	0.040***	0.062***
	(0.0057)	(0.0137)	(0.0147)
Sample	All	Est. with Deaths	New Hires
Mean of Dep. Var	0.061	0.066	0.137
Observations	5,334,545	411,399	697,496

Notes: Table displays $\hat{\alpha}_1$, $\hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for specification (4). Standard errors are clustered at the origin establishment level. The dependent variable in all regressions is the probability of switching to a the deceased or retired person's last sector of employment. First column includes all workers in either the treatment or the control group, within three years and three years after the death or retirement event. Second column includes all workers in establishments with death. Third column includes only new hires within within all establishments that experience either death or retirement event.

Figure 2: Propensity to Switch Jobs Before vs. After Death and Retirement



Note: Data source: SIEED. Figure plots for all establishments that undergo an actual death or retirement event, the propensity for the incumbent workers to switch to another establishment in the years before and after the event. In particular, figure plots the α estimates in equation (6).

tially higher wages.

Although firm-level productivity itself is not directly observable, we use two outcome variables as proxies. First, we investigate whether workers with a higher number of coworkers from a destination industry demonstrate prolonged job tenure after transitioning into that industry. Secondly, starting from the year 1985 onward, we explore whether these workers are more prone to switch to establishments exhibiting higher firm-level AKM effects.[24] We conduct the following regression analysis on all job switchers who move to a industry different from the one they were just employed in:

$$y_{piet} = \alpha_0 + \alpha_1 \tilde{\theta}_{pjt} + \alpha_2 \frac{1}{T-1} \sum_{k \neq 1} \theta_{pjk} + \zeta_{io(p,t)jt} + \xi_{l(p,t)t} + \Gamma X_{pijt} + \varepsilon_{pijt} \tag{7}$$

where y_{piet} denotes an outcome variable for individual p switching from industry i into an establishment e that belongs to industry j during year t, and all independent variables are defined in the same ways as in the baseline specification (1). Our objective is to explore whether individuals' selection of firms within a specific industry, after deciding to work in that industry, varies based on their information set.

To achieve this, our sample consists of all job switchers transitioning into sector j, and we estimate

[24] We link the establishment fixed effects estimated by at the research Data Center (FDZ) of the German Federal Employment Agency at the Institute for Employment Research (IAB). The estimation strategy follows Abowd, Kramarz and Margolis (1999) and the estimation on time periods used for our setting is generously made available by Bellmann et al. (2020). The firm and person fixed effects according to AKM are estimated for 5 periods: 1985-1992, 1993-1999, 1998-2004, 2003-2010 and 2010-2017.

the regression by pooling observations across all destination sectors. In alignment with our baseline analysis, which investigates the impact of coworker information on sectoral choices, we include as regressor the difference between the current-year and the non-current-year coworker shares for each individual that were last employed in a destination sector. We also include the non-current-year coworker shares for each individual that were last employed in a certain sector to control for the overall difficulty of transition between the individual's current establishment of employment and that destination sector. Because we would like to test whether individuals can bring up the likelihood of their current workers transitioning to a high-quality firm within their last sector of employment even when they were previously employed in other firms possibly not of the same quality, our analysis includes coworker shares from the destination industry of interest and not necessarily the destination firm itself. Additionally, we introduce fixed effects to control for time-varying shocks specific to the origin and destination industries, as well as changing transition barriers between each industry pair. We include occupation-by-origin-by-destination fixed effects to address challenges in transitioning to higher-quality firms for certain occupations within a fixed industry pair. Furthermore, we account for location-by-time fixed effects to distinguish supply-side influences affecting individuals' ability to move into a high-quality establishment. Standard errors are clustered at the origin establishment level, considering the correlation of choices by job switchers currently employed in the same firm.

Table 3 presents the results of estimating regression (7) with firm fixed effects and tenure at the new job as the independent variables. When controlling for the non-current-year coworker share and a comprehensive list of individual-level and industry-level covariates, increasing from the destination sector in an individual's origin establishment, increasing the current-year coworker share from 0 to 1 corresponds to the individual moving to a firm with a firm fixed effect quantile that is, on average, 0.133 higher and extending their tenure in the new firm by an average of 5 months. Our results are consistent with the conjecture that the influence of coworker networks extend beyond sectoral choices. Apart from enhancing their probability to move to a potential destination sector, having more coworkers from that sector also enables workers to gain better information on the firm quality within the sector.

2.5 Taking Stock

Our empirical analyses reveal positive and statistically significant relationships between the composition of coworkers from specific sectors and individuals' propensity to transition to those sectors, including their elasticity to potential wage gains. This influence extends to workers' firm choices, with a higher proportion of coworkers from a particular sector associated with selection of higher-quality firms and longer tenure.

Our approach controls for various confounding factors, including similarities in labor demand between sectors and time-varying shocks affecting occupational transitions. The findings remain robust across alternative definitions of coworkers, wage imputation methods, and sample selection criteria. This relationship persists across diverse worker demographics, wages, nationalities, and tenure levels.

Table 3: Impact of Coworkers on Firm Quality of Sector Switchers

	Firm Wage FE	Firm Wage FE	Tenure at New Job	Tenure at New Job
Current-year Coworker	0.133***	0.139***	0.458***	0.471***
	(0.0110)	(0.0113)	(0.0153)	(0.0104)
Non-current-year Coworker	0.723***	0.713***	0.531***	0.545***
	(0.0197)	(0.0193)	(0.0094)	(0.0104)
AKM Person FE		✓		✓
Mean of Dep. Var	12.4	12.4	1.92	1.92
R^2	0.39	0.40	0.121	0.13
Observations	8,743,260	7,882,124	11,010,158	8,236,194

Notes: Table displays $\hat{\alpha}_1$ and $\hat{\alpha}_2$ estimated for specification (7). Standard errors are clustered at the origin establishment level. The dependent variable for columns (1) - (2) is the firm fixed effect quantiles estimated from an AKM regression at the new job. Firms are categorized into 20 quantiles in total. The dependent variables for columns (3) - (4) is the tenure at the new job. Columns (2) and (4) control for the person fixed effect quantiles estimated from an AKM regression for each job switcher and the logged wage at the new job.

Moreover, the empirical patterns hold when analyzing different subsets of the workforce: all workers in the economy, job switchers only, job switchers with non-top-coded wages, and those who do not switch states. An IV analysis using unexpected coworker death and retirement further corroborates these results, strengthening our confidence in the observed relationships.

Given our comprehensive controls and IV design, these results go beyond suggestive statements about equilibrium relationships in canonical sectoral choice models with exogenous adjustment costs. This mechanism can play important roles when evaluating sectoral shocks, deviating from insights in standard models. For instance, it suggests asymmetric responses to positive versus negative sectoral shocks. Positive shocks may reduce worker outflow, necessitating governmental intervention for smoother transitions. Negative shocks present a more nuanced scenario with opposing forces, making appropriate policy responses unclear ex-ante.

The causal relationship we uncover between coworker networks and sectoral choice decisions calls for careful examination when evaluating the propagation of sector-specific shocks. Building on these empirical findings, we propose a theoretical framework of sector and job choice, where coworker composition influences both perceived productivity and transition costs. This framework allows us to quantify the influence of coworker networks on sectoral labor transition dynamics, in particular within the context of a shock similar to COVID-19.

3 A Model of Job Choice under Coworker Influences

Our reduced form analysis documents that coworkers exert a significant influence on job choices across sectors, helping shape sectoral reallocation. The observed patterns raises critical questions: to what extent does sectoral mobility trigger further sectoral mobility? What are the implications for aggregate welfare and production when individuals overlook the externalities of their job-transition behaviors on other workers in the economy? To address these questions, we delve into a model.

3.1 Environment

Time is infinite and continuous. The economy consists of N distinct sectors indexed by k, n or h.[25] A sector n has M_n firms. There are S firms in the economy, and the firms are indexed by i, j, r or d.[26] The set of sectors is denoted by $\mathcal{N}$ and the set of firms within a sector n is denoted by $\mathcal{M}_n$. All firms within a sector produce perfectly substitutable goods. A firm has a constant, firm-specific productivity level. In addition to the firm-level productivity, a sector n features a fixed component of productivity level $\tilde{Z}^n$, representing the baseline productivity within a sector that underpins the persistent component of sectoral wage. In each period, each sector is subject to a sectoral productivity shock Z_t^n.

Assumption 1. *The sectoral productivity shock follows an Ornstein–Uhlenbeck process*

$$d\log\frac{Z_t^n}{\tilde{Z}^n} = -\eta\log\frac{Z_t^n}{\tilde{Z}^n}dt + \epsilon^n\delta^n dW_t$$

where dW_t denotes the Wiener Process. $\tilde{Z}^n$ represents the sectoral-specific scale of the aggregate TFP shock, and δ^n represents the sectoral-specific volatility of the shock. We re-scale the aggregate shock for each sector by writing:

$$z_t = \frac{1}{\epsilon^n\delta^n}\log\frac{Z_t^n}{\tilde{Z}^n} \Rightarrow Z_t^n = \tilde{Z}^n\exp(\epsilon^n\delta^n z_t)$$

such that z_t follows an Ornstein-Uhlenbeck process with unit variance:

$$dz_t = -\eta z_t dt + dW_t$$

When $Z_t = \exp(z_t)$:

$$d\log(\frac{Z_t}{\tilde{Z}}) = -\eta\log(\frac{Z_t}{\tilde{Z}})dt + dW_t$$

Production A firm j in sector n produces a good that is perfectly substitutable with the goods produced by any other firm in sector n, and has a firm-specific productivity level B^{jn} that is fixed over time and a productivity z_t^n that is common to all firms in that sector. The firms in each sector can produce varieties of the intermediate good, requiring inputs from labor only. We assume that the firm-level production function takes on the form:

$$Y_t^{jn} = B^{jn}Z_t^n(L_t^{jn})^{1-\gamma},\ \gamma > 0 \tag{8}$$

[25] We need 3 subscripts to index sectors. For instance, we need both k and n to index the flow from n to k, and an additional letter h to denote other sectors in the economy that are also options when workers make their job-switching decisions.

[26] We need 4 subscripts to index firms. As a concrete example, we use ik and rk to index two firms within sector k when calculating cross-firm flows within the same sector k, and jn to index one firm in another sector n when calculating sector-level flows from n to k. Finally, we denote by dh an additional firm in a sector other than the reference sector pair, as the fraction of workers moving from n to k depends on the inclusive values of moving into other sectors in the economy.

where the productivity level A_t^{jn} for a firm j in sector n is equal to the product of the firm-specific component B^{jn} and the sector-specific component Z_t^n of TFP. We normalize the firm-specific component of TFP such that the average B^{jn} across all firms within each sector n is equal to 0. The production features decreasing marginal returns to labor. Firms within a certain sector requires identical shares of factors of production, and only differ in their fixed firm-specific productivity level. A firm jn maximizes its profit by solving:

$$\max_{L_t^{jn}} \; p_t^n Y_t^{jn} - w_t^{jn} L_t^{jn}$$

which yields the expression for wage of firm jn as a function of its employment L_t^{jn}, the sectoral good price p_t^n, and other model fundamentals and parameters:

$$w_t^{jn} = p_t^n (1-\gamma) B^{jn} Z_t^n (L_t^{jn})^{-\gamma} \tag{9}$$

A firm in this economy makes a profit that is equal to $\gamma p_t^n Y_t^{jn}$. We assume that profits made in each firm will be collected and redistributed to workers in that firm through a proportional subsidy τ_t, and workers earn a de facto wage of $(1+\tau_t) w_t^{jn}$ at time t. It is straightforward to show that τ_t is fixed at the level of $\frac{\gamma}{1-\gamma}$ across time.

Workers The economy starts with mass L_0^{jn} of workers at the combination of firm j in sector n. A worker supplies one unit of labor inelastically to receive a sectoral wage w_t^{jn}, and all workers employed in the same firm will allocate consumption in the same way. For a worker employed in firm j of sector n, she allocates consumption over goods from all sectors using a Cobb-Douglas aggregator:

$$c_t^{jn} = \Pi_{k=0}^{N} (c_t^{jn,k})^{\chi^k} \tag{10}$$

where $c_t^{jn,k}$ is the consumption of sector-k goods for a household employed in jn. The exponents representing consumption shares of the sectoral goods sum up to 1, $\sum_{k \in \mathcal{N}} \chi^k = 1$. The price index is therefore given by:

$$P_t = \Pi_{j,n} \left[p_t^n / \chi^n \right]^{\chi^n} \tag{11}$$

where p_t^{jn} is the price of goods purchased from firm j of sector n. Consumption for a worker employed in firm j of sector n is given by:

$$c_t^{jn} = (\frac{1}{1-\gamma}) w_t^{jn} / P_t \tag{12}$$

We assume that agents have log utility. Using the relationship between wages and prices in equations 9 obtained from firm optimization, we can write the utilities for those employed in firm jn as a function of model primitives, the total amount of labor in that firm, and the sectoral price:

$$u(c_t^{jn}) = \log(B^{jn}) + \log(Z_t^n) - \gamma \log(L_t^{jn}) + \log(p_t^n (1-\gamma)/P_t) + \log(\frac{1}{1-\gamma})$$

Prices are at the levels that ensure supplies and demands of goods are equalized:

$$\chi^k \sum_{n\in\mathcal{N}} \sum_{j\in\mathcal{M}_n} p_t^n Y_t^{jn} = p_t^k \sum_{i\in\mathcal{M}_k} Y_t^{ik} \tag{13}$$

In addition to consuming goods, individuals also provide labor to a specific firm within a particular sector. They have the option to switch to a different firm at any time, but such transitions come with associated costs. Drawing inspiration from our reduced-form analysis, we depart from the conventional assumption of invariant transition costs typically found in discrete-choice models. Instead, in our framework, transition costs are contingent upon both the proportion of workers migrating from any given firm within sector k to jn, as well as from firm ik to jn, and exhibit a negative correlation with these fractions.

Assumption 2. *The cost for labor reallocation from firm j in sector n to firm i in sector k costs $\kappa_t^{jn,ik}$. These costs are time variant, additive, and measured in terms of utility. Formally:*

$$\kappa_t^{jn,ik} = (1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k} + (1-\alpha_1 l_t^{ik,jn})\bar{\kappa}^{jn,ik} \tag{14}$$

where $\bar{\kappa}^{n,k}$ is a term capturing the common time-invariant adjustment cost from any firm jn to sector k in year t, and $\bar{\kappa}^{jn,ik}$ characterizes the baseline time-invariant adjustment cost that is specific to the firm jn, ik transition and is not captured by the sector-level adjustment cost, $\bar{\kappa}^{n,k}$. $l_t^{k,jn} = \sum_{i\in\mathcal{M}_k} \frac{\mu_t^{ik,jn} L_t^{ik}}{L_t^{jn}}$ is the share of workers in firm jn that just transitioned from any firm in sector k and $l_t^{ik,jn} = \frac{\mu_t^{ik,jn} L_t^{ik}}{L_t^{jn}}$ is the share of workers in firm jn that just transitioned from firm ik. α_0 and α_1 are parameters characterizing the importance of origin-sector-specific and origin-firm-specific coworkers on adjustment costs.

Assumption 2 assumes that higher previous flows from a particular sector tend to predispose incumbent workers towards transitioning to that sector. This predisposition could stem from factors such as coworkers bringing valuable skills or connections from their previous workplaces, thereby reducing the time and effort required for such transitions. Importantly, future sector- and job-choice decisions are dependent on the current flows across sectors and firms, which are endogenous model objects. If we failing to the account for the pattern that labor reallocation further engenders labor reallocation because of the existence of the coworker network, we may be incorrectly attributing changes in flows solely to the time-invariant component of bilateral labor adjustment costs.

Apart from labor adjustment costs, workers' decisions regarding which firm and sector to work in are influenced by an additive idiosyncratic shock for each choice, denoted by ϵ_t^{ik} if the worker moves to firm i in sector k at time t. All workers discount future outcomes at a rate of ρ. The taste shocks are scaled by a parameter ν. Additionally, we assume that the taste shocks can be decomposed into a sector-specific component and a firm-specific component. Taste shocks are uncorrelated for firm choices across sectors but are approximately correlated by $1-\zeta$ across all firms within the same sector, for each sector.

Assumption 3. *For each firm j in a sector n, the taste shock can be decomposed into:*

$$\epsilon_t^{jn} = \epsilon_{0,t}^{n} + \zeta \epsilon_{1,t}^{jn}$$

where $\epsilon_{1,t}^{jn}$ is a firm-specific component and $\epsilon_{0,t}^{n}$ is common to all firms within the same sector. Both $\epsilon_{1,t}^{jn}$ and $\epsilon_{0,t}^{n}$ are distributed according to EV1 with mean 0 and variance $\frac{\pi^2}{6}$.

At any given moment, workers can transition into another firm at the rate ϕ. The parameter $\phi < 1$ reflects the tendency for most workers to remain in their current positions. Additionally, we introduce an assumption where the perceived sector-specific and firm-specific components of Total Factor Productivity (TFP) are contingent on the respective shares of coworkers who have recently transitioned from the sector and the firm. This assumption is inspired by our reduced-form analysis, indicating that the composition of coworkers within a specific firm can impact not only the average rate of job switching but also the responsiveness of incumbent workers to potential wage disparities across different destination sectors.

We posit that beyond simply influencing the average propensity to transition to a particular sector, the composition of coworkers' previous sectors and current employers also impacts the elasticity of workers' decisions regarding both sector and firm components of the TFP. Consequently, coworker composition would influence the elasticity of moving propensity to the wage at the destination, a prediction that's consistent with our reduced-form findings.

Assumption 4. *Workers within the same firm share identical beliefs on the firm- and sector-specific components of TFP. The accuracy of their beliefs increases with the share of current coworkers that just transitioned from in the potential destination sector of employment. Denote the expected logged firm-level TFP for firm ik held by workers in firm jn at time t as $\hat{b}_t^{jn,ik}$ and the expected logged sector-level TFP for sector k held by workers in firm jn as $\hat{z}_t^{jn,k}$, then we assume:*

$$\hat{z}_t^{jn,k} = \beta_0 l_t^{k,jn} \log(Z_t^k) + (1 - \beta_0 l_t^{k,jn})\bar{z} \tag{15}$$

$$\hat{b}_t^{jn,ik} = \begin{cases} \beta_1 l_t^{k,jn} \log(B^{ik}) & \text{if } jn \neq ik \\ \log(B^{ik}) & \text{if } jn = ik \end{cases} \tag{16}$$

where $\bar{z}$ is the mean of the logged sector-specific components of TFP across all sectors, and the mean of the firm-specific components of TFP across all firms within the sector k is equal to 0. β_0 and β_1 are parameters determining the strengths of coworkers influences on move elasticity with respect to productivity in the destination firm and the destination sector. For a worker's own firm, we assume that she knows perfectly the firm-level TFP, so this belief is not a function of the fraction of job stayers.

Assumption 4 specifies that each worker's perception of the TFP of a sector is a weighted average of the actual TFP for that sector and the mean TFP level across all sectors in the economy. The presence of more coworkers who have recently transitioned from a particular sector within an establishment enhances the accuracy of its workers' beliefs regarding the productivity level of that sector. Conversely, in the absence of any coworkers from that sector, workers are unable to differentiate it from other sectors in the economy and must rely solely on the economy-wide average to infer its productivity level. The same principle applies to beliefs regarding firm-level TFPs: workers develop more accurate beliefs for the productivity of a potential destination firm as their shares of coworkers last employed in that firm's sector increase.[27] Without any coworkers from a certain sector, workers form beliefs using the sector-wide average productivity.[28]

The timing for the worker's problem and decisions unfolds as follows: Workers observe the average sector-level productivity across all sectors in the economy, as well as the average firm-level productivity across all firms within each sector. If a worker is employed, she earns the wage offered by her firm. With probability ϕ, the worker chooses whether or not to switch jobs. During the job switching decision, both her perceived productivity level at the destination firms and her adjustment cost depend on the share of her coworkers at the current firm that recently switched from the destination firm. The job choice decision is made in two consecutive steps: Firstly, workers select which sector they'd prefer to work in based on their perceived levels of sector- and firm-level productivity, their labor adjustment costs to different destination firms, and the realizations of taste shocks. Secondly, once they choose a certain sector, workers become fully aware of the sector-specific productivity associated with that sector, and then consider which firm within the sector to work in. All agents are assumed to be rational except regarding compensation levels and are fully aware of coworker share compositions. The Hamilton-Jacobi-Bellman (HJB) equation for an individual employed in firm j of sector n can therefore be written as consisting of the current-time utility and the continuation value of having the possibility of moving to any other firm in the economy:

$$\rho v_t^{jn} - \mathbb{E}[\frac{dv_t^{jn}}{dt}] = u(c_t^{jn}) + \phi \left\{ \max_{d,h} \mathbb{E}[v_t^{dh}] - \kappa_t^{jn,dh} + \nu \epsilon_t^{dh} - v_t^{jn} \right\} \tag{17}$$

where v_t^{jn} is the lifetime utility of a worker currently employed in firm j of sector n. We let $V_t^{ik} = \mathbb{E}[v_t^{dh}]$ represent the actual, current expected value obtainable from working in firm i of sector k by the worker currently employed in firm j of sector n, where the expectation is taken over idiosyncratic

[27] Our reduced-form analysis suggests that having more coworkers from a certain sector is associated with moving to a better-quality firm within that sector, conditional on already choosing that sector. Therefore, we assume that the expectation of firm-level productivity is a function of the share of coworkers from a certain sector, as opposed to the specific firm.

[28] We assume that the dependence of perceived TFP and adjustment cost on one's coworker networks extends to own-sector transitions. Based on an alternative version of the baseline specification that includes within-sector job switchers, the coefficients on the non-current-year coworker share as well as its interaction with the wage differential both remain statistically significant and stable in magnitudes with the one with only cross-sector transitions, suggesting the same relationship holds even for individuals that attempt to transition within their current sector. This can also be justified by that coworkers from the same sector might bring varied experiences from different companies or sub-industries, potentially influencing one's belief about wages in their own sector, and that this approach ensures consistency in modeling by applying the same logic to all sectors.

taste shocks.[29] The taste shocks are scaled by a parameter ν. We now derive the expected lifetime utility from working in a firm jn as well as the aggregated flow from firm jn to firm ik.

Proposition 1. *The expected value V_t^{jn} of being in firm j of sector n satisfies the HJB equation:*

$$\begin{aligned}\rho V_t^{jn} =& u(c_t^{jn}) + \mathcal{L}[V] + \mathbb{E}[\frac{dV_t^{jn}}{dt}], \\ \mathcal{L}[V] \equiv& \phi\Bigg\{\nu \log \sum_{h\in\mathcal{N}} \exp\Bigg(\zeta \log \sum_{d\in\mathcal{M}_h} \exp\Big[\frac{1}{\nu\zeta}\Big(V_t^{dh} - \frac{1-\beta_1^{jn,dh} l_t^{h,jn}}{\rho+\phi}\log(B^{dh}) - (1-\alpha_1 l_t^{dh,jn})\bar{\kappa}^{jn,dh}\Big)\Big] + \\ & \frac{1-\beta_0 l_t^{k,jn}}{\rho+\phi}\Big(\bar{z} - \log(Z_t^h)\Big) - (1-\alpha_0 l_t^{h,jn})\bar{\kappa}^{n,h}\Bigg) - V_t^{jn}\Bigg\}\end{aligned} \tag{18}$$

The sector- and firm-level flows are given by:

$$\mu_t^{jn,k} = \frac{\exp\Big(\zeta S_t^{jn,k} + \frac{1-\beta_0 l_t^{k,jn}}{\nu(\rho+\phi)}(\bar{z} - \log(Z_t^k)) - \frac{1}{\nu}(1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k}\Big)}{\sum_{h\in\mathcal{N}}\exp\Big(\zeta S_t^{jn,h} + \frac{1-\beta_0 l_t^{h,jn}}{\nu(\rho+\phi)}(\bar{z} - \log(Z_t^h)) - \frac{1}{\nu}(1-\alpha_0 l_t^{h,jn})\bar{\kappa}^{n,h}\Big)} \tag{19}$$

$$\mu_t^{jn,ik|k} = \frac{\exp\Big(V_t^{ik} - \frac{1-\beta_1^{jn,ik} l_t^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_t^{ik,jn})\bar{\kappa}^{jn,ik}\Big)^{\frac{1}{\nu\zeta}}}{\sum_{r\in\mathcal{M}_k}\exp\Big(V_t^{rk} - \frac{1-\beta_1^{jn,rk} l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_t^{rk,jn})\bar{\kappa}^{jn,rk}\Big)^{\frac{1}{\nu\zeta}}} \tag{20}$$

where

$$S_t^{jn,h} = \log\Bigg[\sum_{d\in\mathcal{M}_h}\exp\Bigg(\frac{1}{\nu\zeta}\Bigg(V_t^{dh} - \frac{1-\beta_1^{jn,dh} l_t^{h,jn}}{\rho+\phi}\log(B^{dh}) - \Big(1-\alpha_1 l_t^{dh,jn}\Big)\bar{\kappa}^{jn,dh}\Bigg)\Bigg]$$

The labor distribution evolves according to the Kolmogorov Forward (KF) equation:

$$\frac{\partial L_t^{jn}}{\partial t} = \phi[\sum_{k\in\mathcal{N}}\sum_{i\in\mathcal{M}_k}\mu_t^{ik,jn}(\mu_t, V_t)L_t^{ik} - L_t^{jn}] = \Big(\phi[(\mu^*(\mu_t, V_t) - Id)L_t]\Big)_{jn} \equiv \Big(L^*(\mu, V)L_t\Big)_{jn} \tag{21}$$

where $\mu_t^{jn,ik} = \mu_t^{jn,k} \times \mu_t^{jn,ik|k}$ is the product of the sector choice and the firm choice probabilities. μ^* denotes the matrix transpose of the transition matrix μ. We denote by $L^*(V) = \phi(\mu^*(\mu, V) - Id)$.

Proof. See Appendix D.1. □

Compared to standard dynamic job choice models with exogenous job transition costs, our model introduces a novel feature: job transitions are influenced by the proportion of coworkers from the target firm or sector. This coworker composition serves a dual role.

Firstly, it affects responsiveness to sectoral productivity changes. In Equation (19), the elasticity

[29] Note that this refers to the expectation of an agent with correct perception of the sector-and firm-specific TFP, as opposed to the workers in our model where perceived TFP depends on the coworker composition.

for workers in firm jn transitioning to sector k is attenuated by $\frac{1-\beta_0 l_t^{k,jn}}{\nu(\rho+\phi)}$, which decreases as the share of coworkers from sector k diminishes. Similarly, in Equation (20), the elasticity of firm choice within a sector is dampened by $\frac{1-\beta_1 l_t^{k,jn}}{\nu(\rho+\phi)}$.

Secondly, coworker shares impact the level of job flows. This is reflected in equations (19) and (20) through terms $(1-\alpha_0 l_t^{k,jn})$ and $1-\alpha_1 l_t^{ik,jn}$, which multiply the time-invariant components of transition costs, $\bar{\kappa}^{n,k}$ and $\bar{\kappa}^{jn,ik}$. This mechanism further suppresses bilateral flows between sector pairs with high skills transition barriers.

Our model illustrates a feedback loop wherein increased cross-sector labor flows lead to higher overall mobility. This relationship is evident in the labor transition equation, where inflows appear on the right-hand side. The feedback loop operates by reducing adjustment costs for transitions to sectors where job switchers were previously employed and increasing responsiveness to wage changes in those sectors. Consequently, initial cross-sector movements not only reflect inherent transition difficulties but also stimulate further mobility, fostering self-sustaining job flows within the economy.

This feedback mechanism is captured in the equations governing sector- and firm-level transitions. In equations (19) and (20), the outflow from sector j, firm n to sector i, firm k at any given time depends on both the firm-level inflow from ik to jn and the sector-level inflow from any firm in sector k to jn. By combining these two mobility equations, we can derive the labor transition matrix. Solving for labor transition therefore involves finding a fixed point to the following:

$$\mu_t^{ik,jn} = \Omega^{ik,jn}(\mu_t, z_t, V_t(\mu_t)) = \mu_t^{ik,jn|n} \times \mu_t^{ik,n} \tag{22}$$

where

$$l_t^{n,ik} = \sum_{r\in\mathcal{M}_n} \frac{\mu_t^{rn,ik} L_t^{rn}}{L_t^{ik}}, \quad l_t^{jn,ik} = \frac{\mu_t^{jn,ik} L_t^{jn}}{L_t^{ik}}$$

$$\mu_t^{ik,jn|n} = \frac{\exp\left(V_t^{jn} - \frac{1-\beta_1 l_t^{n,ik}}{\rho+\phi}\log(B^{jn}) - (1-\alpha_1 l_t^{jn,ik})\bar{\kappa}^{ik,jn}\right)^{\frac{1}{\nu\zeta}}}{\left[\sum_{r\in\mathcal{M}_n}\exp\left(V_t^{rn} - \frac{1-\beta_1 l_t^{n,ik}}{\rho+\phi}\log(B^{rn}) - (1-\alpha_1 l_t^{rn,ik})\bar{\kappa}^{ik,rn}\right)^{\frac{1}{\nu\zeta}}\right]}$$

$$\mu_t^{ik,n} = \frac{\exp\left(\zeta S_t^{ik,n} + \frac{1-\beta_0 l_t^{n,ik}}{\nu(\rho+\phi)}(\bar{z} - \log(Z_t^n)) - \frac{1}{\nu}(1-\alpha_0 l_t^{n,ik})\bar{\kappa}^{k,n}\right)}{\sum_{h\in\mathcal{N}}\exp\left(\zeta S_t^{ik,h} + \frac{1-\beta_0 l_t^{h,ik}}{\nu(\rho+\phi)}(\bar{z} - \log(Z_t^h)) - \frac{1}{\nu}(1-\alpha_0 l_t^{h,ik})\bar{\kappa}^{k,h}\right)}$$

$$S_t^{ik,h} = \log\left[\sum_{d\in\mathcal{M}_h}\exp\left(\frac{1}{\nu\zeta}\left(V_t^{dh} - \frac{1-\beta_1 l_t^{h,ik}}{\rho+\phi}\log(B^{dh}) - \left(1-\alpha_1 l_t^{dh,ik}\right)\bar{\kappa}^{ik,dh}\right)\right]$$

The coworker mechanism has asymmetric implications for responses to positive versus negative sectoral shocks. A positive shock decreases outflows from the sector, resulting in lower inflows compared to the optimum. Conversely, a negative shock increases outflows, creating two opposing forces: one reducing transition costs and increasing inflows, and another decreasing inflows as workers become more aware of the sector's declining TFP. [30]

3.2 Steady State

We are now ready to define the equilibrium concepts for this model. At a certain instance in time, the endogenous state of the economy is characterized by the distribution of labor across all firms L_t. The fundamentals of the economy can be classified into two categories: constant and time-varying. The constant fundamentals in the economy are firm-specific productivity distribution $\{B^{jn}\}_{j=1,n=1}^{M_n,N}$, and unemployment insurance b. The time-varying fundamentals are sector-specific productivity distribution $\{Z_t^n\}_{n=1}^N$ and the shared components of the labor reallocation costs $\{\bar{\kappa}^{n,k}\}_{j=1,n=1,k=1}^{M_n,M_k,N}$. The parameters in our model are the extent of decreasing returns to labor γ, the consumption expenditure shares $\{\chi^n\}_{n=1}^N$, the sector-specific scale of the productivity shock $\{\delta^n\}_{n=1}^N$, the worker discount rate ρ, the parameter characterizing correlation of taste shocks within a sector ζ, the job transition probability upon receiving a taste shocks ϕ, and the job choice elasticity ν, and the dependence of adjustment costs on coworker shares α_0, α_1 as well as the dependence of perceived TFP on coworker share β_0, β_1. We denote the constant fundamentals by $\bar{\Theta}$, and the time-varying fundamentals by Θ_t. We define the sequential equilibrium and the stationary equilibrium of the model, given the values of the model parameters.

Definition Given $\{L_0, \Theta_t, \bar{\Theta}\}$, a *sequential equilibrium* of model is a collection of $\{L_t, \mu_t, V_t, w_t\}_{t=0}^{\infty}$ such that:

- All firms maximize profits, so that wages and sectoral goods prices satisfy (9);
- All workers maximize utility according to equation (18);
- Goods market clear for each sector according to equations (11), (12), and (13).
- Labor distribution across sectors and firms evolves according to equations (19), (20), and (21).

Suppose that the sector-level TFP remains unchanged in the economy, then we can define a stationary equilibrium where all endogenous aggregate variables are also constant over time. It follows that in a stationary equilibrium, individual workers may still move across sectors and firms because of their instantaneous taste shocks, but in the aggregate, inflows equal outflows and the labor employed at each firms remains unchanged.

Definition A *stationary equilibrium* of the model is a sequential competitive equilibrium such that the endogenous model objects $\{L_t, \mu_t, V_t, w_t\}$ remain constant at all time t.

[30]The force that decreases inflows when experiencing a negative sectoral shock is stronger for sectors with higher TFP. For example, Figure F1 is an illustrative example for a negative sectoral shock. The difference between the own-sector labor impulse response when the sector experiences a negative is smaller for the service sector (relatively higher TFP) vs. for the construction sector (relatively lower TFP).

At the stationary equilibrium, time derivatives are all equal to zero. Workers' HJB equations satisfy

$$\rho V_{ss}^{jn} = u(c_{ss}^{jn}) + \mathcal{L}[V_{ss}^{jn}] \tag{23}$$

The labor distribution across firms satisfies:

$$0 = L^*(\mu_{ss}, V_{ss})L_{ss} \tag{24}$$

3.3 The Master Equation, the FAME, and the Transition Dynamics

Our framework characterizes a dynamic general equilibrium economy in which the distribution of workers $L_t = \{L_t^{jn}\}_{j,n}$ are the aggregate state variables. Given a labor distribution, we can determine the wage at each firm as well as the price for each sectoral good using firm maximization and market clearing conditions. The distribution of workers across firms in different sector evolves according to the law of motion in (21), which can be solved as a fixed point according to equations (19) and (20), given the expected values of being employed in each potential firm in the economy. Solving for the transitional dynamics in such framework can be computationally challenging since the solution of the model equilibrium are conditional on the values of the fundamentals at each firm. Besides, given that we embed a coworker network into the model, the labor transition matrix is not easily obtainable given the distribution of value functions. We therefore turn to the "Master Equation" technique developed in Bilal (2021), by focusing on local perturbations around a deterministic steady state.

The Master Equation In the Master Equation approach, we treat the labor distribution as high-dimensional state variables for worker maximization. We then write the value function $V^{jn} = V^{jn}(z, L)$, where the value function is dependent only on the state variables and we can eliminate the time subscript t. Using the chain rule, we write the first-order approximation of the continuation value resulting from changes in the state variables as:

$$\mathbb{E}[\frac{dV^{jn}}{dt}] = \mathcal{A}_\epsilon(z)[V^{jn}] + \sum_{k\in\mathcal{M}}\sum_{i\in\mathcal{M}_k} \frac{\partial V^{jn}}{\partial L^{ik}}\frac{dL^{ik}}{dt} \tag{25}$$

The first term, $\mathcal{A}_\epsilon(z)$ embeds the continuation value stemming from the sectoral shocks. Given Assumption 1, $\mathcal{A}_\epsilon(z)[V] = -\eta z\frac{\partial V}{\partial z} + \frac{\epsilon^2}{2}\frac{\partial^2 V}{\partial z^2}$. The second term represents the change in this value with respect to the labor distribution across sectors. Worker reallocation across sectors and firms will lead the distribution of wages and prices of sectoral goods to change, which then impact the employees at firm jn. Combing with the evolution of labor over time, specified in equation (21), we can then obtain the workers' Master Equation:

$$\rho V^{jn}(L) = u^{jn}(L) + \mathcal{L}^{jn}[V] + \sum_{i\in\mathcal{M}_k}\sum_{k\in\mathcal{N}} \frac{\partial V_t^{jn}}{\partial L^{ik}} L^{ik*}(\mu, V)[L] + \mathcal{A}_\epsilon(z)[V_t^{jn}] \tag{26}$$

where the first term represents the flow payoff. The second term characterizes workers' continuation value from having the probability of moving to another firm in the economy. The third term characterizes the continuation value from changes in the labor distribution. When individuals switch jobs, the distribution of wages and prices of sectoral goods also shifts, which affects their future job-switching decision and the values obtainable by switching to another firm in the economy. Finally, the last term represents the continuation value arising from the shocks to the productivity in each sector. Solving the value function V according to the Master Equations (26) and the labor distribution L according to the law of motion (21) suffices for finding the equilibrium of the economy.

The FAME The Master Equation is a succinct representation of the model equilibrium. Nevertheless, solving for the fully nonlinear Master Equations (25) can still be numerically challenging since it depends on high-dimensional object, the labor distribution and the labor transition. We therefore turn to a local perturbation method. By coming up with a closed form characterization of the linearized Master Equation, we reduce the number of dimensions to keep track of for this problem.

Following the method developed in Bilal (2021), we solve the First-order Approximation to the Master Equation (FAME). To do this, we Taylor expand the Master equation in ϵ around the steady state. The shocks are assumed to be close enough to the steady state, so that $L = L_{ss} + \epsilon n$, where n is the scaled deviations of the labor distribution from the steady state. We then look for a solution by conducting a first-order Taylor expansion in ϵ:

$$V_t^{jn}(z, L_{ss} + \epsilon n) = V_{ss}^{jn} + \epsilon \Big\{ \sum_{i \in \mathcal{M}_k} \sum_{k \in \mathcal{N}} v^{jn,ik} n^{ik} + \omega^{jn} z \Big\}$$

Instead of solving for the exact value function V in the Master Equation, our current approach involves solving for the directional derivatives v and ω of the value function with respect to the distribution.

Proposition 2. *The deterministic FAME can be written as:*

$$\rho v = \bar{v} + Lv + vL^* + vGv + vQ \tag{27}$$

The stochastic FAME can be written a:

$$\rho \omega = \bar{\omega} + L\omega + vG\omega + vH + \mathcal{A}(z)[\omega z] \tag{28}$$

where μ is the firm-level transition matrix and the remaining terms are given by:

$$\bar{v} = \frac{1}{P_{ss}} diag\big(u'(c_{ss})\big) J - \frac{1}{P_{ss}^2} diag\Big(u'(c_{ss})\bar{Q}\Big) diag\Big(w_{ss}\Big)$$

$$\bar{\omega} = \frac{1}{P_{ss}} diag\big(u'(c_{ss})\big) \bar{J}^z \bar{Z} - \frac{1}{P_{ss}} diag\big(u'(c_{ss})\bar{Q}^z \bar{Z}\big) diag\big(w_{ss}\big)$$

$$G = \phi\psi\tilde{R}, \quad Q = \phi\psi\tilde{R}^L, \quad H = \phi\psi\tilde{R}^z\bar{Z}$$

J is the matrix consisting of entries $\frac{\partial w^{jn}}{\partial L^{ik}}$. $\bar{Q}$ is the matrix in which every row is the vector consisting of entries $\frac{\partial P}{\partial L^{ik}}$. $\bar{Q}^z$ the matrix that duplicates the row vector $[Q^z_{1,1}, \cdots, Q^z_{1,1}, Q^z_{1,2}, \cdots, Q^z_{1,2}, \cdots, Q^z_{1,N}, \cdots, Q^z_{1,N}]$. $\bar{J}^z$ consists of entries $\frac{\partial w^{jn}}{\partial z}$ and $\bar{Q}^z$ consists of entries $\frac{\partial P}{\partial z}$.

In addition, we denote by R^{dh} the vector where each entry corresponds to the derivative of the flow between one pair of firm with respect to the value function of working in any single firm in the economy, by $R^{dh,L}$ the vector where each entry corresponds to the derivative of the flow between a firm pair with respect to the labor distribution, and by $R^{h,z}$ the vector where each entry characterizes the derivative of the flow with respect to the change in the TFP associated with any specific sector: and by $\tilde{R}$, $\tilde{R}^L$, and $\tilde{R}^z$ the matrices after stacking as columns all the R^{dh}'s and the $R^{h,z}$'s.

Finally, we let $\bar{Z}$ be the vector collecting all the sector-specific shocks and ψ by a matrix consisting of $0'$s and $1'$s that sum over all the to collapse $\tilde{R}$ and $\tilde{R}^z$ into the correct relevant dimension:

$$\bar{Z} = [\delta^1 Z^1, 0, \cdots, 0, \delta^2 Z^2, 0, \cdots, 0, \cdots, \delta^N Z^N, 0, \cdots, 0]'$$

$$\psi = \begin{bmatrix} l_{11}\mathbb{1}_{1\times\tilde{N}} & 0 & 0 & \cdots & 0 \\ 0 & l_{21}\mathbb{1}_{1\times\tilde{N}} & 0 & \cdots & 0 \\ 0 & 0 & l_{32}\mathbb{1}_{1\times\tilde{N}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & l_{M_N N}\mathbb{1}_{1\times\tilde{N}} \end{bmatrix}$$

Proof. See Appendix D.2. □

The first component in the deterministic FAME, $\bar{v}$, is the direct price impact. As the distribution of labor shifts among firms, prices undergo corresponding changes. These price movements, in turn, influence the flow payoff for each worker employed at every firm within the economy. The first term in $\bar{v}$ characterizes how alterations in labor distribution affect flow payoff for a worker in firm jn via their effect on wages in jn, while the second term illustrates how changes in labor distribution shift workers' flow pay off by changing the aggregate price index, which in turn stems from changes in sectoral goods prices.

The second component of the FAME, Lv , represents a partial equilibrium force. When the value of moving to any firm in the economy shifts because of changes in population distribution, workers' job choice decision and the associated valuation also change. This change in workers' value can be fully characterized by the steady-state transition matrix L.[31]

The third component of the deterministic FAME, vL^*, represents a general equilibrium force. As

[31] We can evaluate this partial-equilibrium force using the steady-state transition matrix alone because of the envelope condition. In particular, the valuation of the change in population distribution enters only through its direct impact that is calculated by multiplying the probability of moving into each firm with the change in value in the firm brought about by the change in worker distribution. The indirect effect from the change in the optimal firm choice can be ignored when doing the option value calculation.

an additional worker is employed in firm *ik*, she directly impacts the workers in firm *jn*. Specifically, where this additional worker in firm *ik* will transition to over time matters for firm-*jn* worker's welfare, as it represents the evolution of the state variable. This term characterizes the portion of the decision by workers in firm *ik* that can be explained by the current decision-rules of the workers in the economy, or the steady-state transition matrix. To represent the effect of mass employed in firm *ik* on firm *jn*, we right multiply the impulse value with respect to labor distribution by the transpose of the labor transition matrix.

The fourth component in the deterministic FAME model, vGv, characterizes an additional general equilibrium force. It represents how the values obtained by workers in firm *jn* change as the labor distribution law of motion shifts due to an additional worker in firm *ik*. When the number of workers in firm *ik* changes, the labor law of motion changes for two reasons. First, as the number of employed workers in firm *ik* increases, it affects both wages and prices of goods. Second, unique to our setting, the addition of a worker in firm *ik* alters the coworker network composition, which influences the responsiveness to changes in TFP and the labor adjustment costs for workers in firm *jn*. The first-order impact of an additional worker at each firm on the labor law of motion is summarized by the matrix Gv. Converting this impact back to utility terms, it affects workers at each firm through vGv.

The structure of the stochastic FAME is similar to that for the deterministic FAME. The first component in equation (28), $\bar{\omega}$, characterizes the direct impact of the change in sectoral TFP on workers' utility. When the productivity level in a sector changes, both the wages workers receive and the prices of goods change accordingly, and they pass through to workers' utility through the first and the second term in ω respectively.

The second component of the stochastic FAME, $L\omega$, summarizes the partial equilibrium force arising from the option to move into any firm in the economy as sectoral TFP evolves. Analogous to the deterministic FAME, the impact of the job choice decision of any given worker because of a change in sector-level productivity is fully characterized by the steady-state transition matrix L.

The third and fourth terms represent the general equilibrium forces. $G\omega$ characterizes how the response of workers in firm *ik* to aggregate sectoral TFP shocks influences the values obtainable by workers in firm *jn*. As sector-level productivity distribution changes, wages and goods prices fluctuate, which in turn affect the job transition decisions of workers in firm *ik*. Besides the changes in job choices due to price variations, the sector-level TFP changes can directly impact job decisions. This direct impact is due to the coworker network. Depending on the proportion of coworkers from a specific sector, the sector-level TFP enters into the the labor law of motion beyond merely affecting the value function. This direct response is captured by the matrix H. We left-multiply $G\omega$ by H to represent the influence of the mobility decisions of workers in firm *ik* on the utility of employees in firm *jn*.

Finally, the last component in the stochastic FAME describes how the exogenous changes in sector-level TFP affect workers in the economy over time.

The contribution of the coworker network In our framework, the contribution of the coworker network to the labor evolution can be summarized by a single matrix T, where $T_{ik,jn} = \frac{\partial \mu^{ik,jn}}{\partial \mu^{ms,xq}}$.

$$\frac{\partial \mu^{ik,jn}}{\partial \mu^{ms,xq}} =$$
$$\begin{cases} 0 & \text{if } xq \neq ik \\ -\frac{\mu^{ik,jn}\mu^{ik,s}}{\nu}\Big[\alpha_1 \mu^{ik,ms|s} + \sum_{d\in\mathcal{M}_s}\left(\frac{\beta_1 \log(B^{ds})}{\rho+\phi}\right)\mu^{ik,ds|s} + \left(\frac{\beta_0\left(\log(Z^s)-\bar{z}\right)}{\rho+\phi} + \alpha_0 \bar{\kappa}^{k,s}\right)\Big]\frac{L^{ms}}{L^{ik}} & \text{if } m\neq j,\ s\neq n, \text{ and } xq = ik \\ \frac{\mu^{ik,jn}}{\nu}\Big[\frac{1}{\zeta}\frac{\beta_1}{\rho+\phi}\log(B^{jn}) + (1-\mu^{ik,n})\Big(\frac{\beta_0\left(\log(Z^n)-\bar{z}\right)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,n}\Big) & \\ +\left(1-\frac{1}{\zeta}-\mu^{ik,n}\right)\left(\alpha_1\mu^{ik,mn|n} + \sum_{r\in\mathcal{M}_n}\left(\frac{\beta_1\log(B^{rn})}{\rho+\phi}\right)\mu^{ik,rn|n}\right)\Big]\frac{L^{mn}}{L^{ik}} & \text{if } m\neq j,\ s = n \text{ and } xq = ik \\ \frac{\mu^{ik,jn}}{\nu}\Big[\frac{1}{\zeta}\left(\frac{\beta_1}{\rho+\phi}\log(B^{jn}) + \alpha_1\right) + (1-\mu^{ik,n})\Big(\frac{\beta_0\left(\log(Z^n)-\bar{z}\right)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,n}\Big) & \\ +\left(1-\frac{1}{\zeta}-\mu^{ik,n}\right)\left(\alpha_1\mu^{ik,jn|n} + \sum_{r\in\mathcal{M}_n}\left(\frac{\beta_1\log(B^{rn})}{\rho+\phi}\right)\mu^{ik,rn|n}\right)\Big]\frac{L^{jn}}{L^{ik}} & \text{if } ms = jn \text{ and } xq = ik \end{cases}$$

For example, equation (22) implies that without considering the coworker network, for any firm dh in the economy, $R^{dh} = \Omega^{dh}$, where the ik, jn-th entry of $\Omega^{dh} = \frac{\partial \mu^{ik,jn}}{\partial V^{dh}}$. On the other hand, after incorporating the coworker network channel, each R^{dh} is given by:

$$(Id - T)^{-1}\Omega^{dh}$$

We can therefore gain insights on the general-equilibrium effect of the coworker network by looking into the structure of the matrix, $(Id-T)^{-1}$, which amplifies the general equilibrium effect of worker reallocation across sectors if its norm is greater than 1.[32]

Solving the Impulse Values Proposition 2 shows that all objects in the deterministic FAME can be directly computed using steady-state objects. With L, G, and $\bar{v}$ in the deterministic FAME (27) known, we then seek for the solution for the impulse value that satisfies the following nonlinear Sylvester matrix equation:

$$(\rho \cdot Id - L)v - v[L^* + Gv] = \bar{v} \tag{29}$$

In practice, we solve for v using an iterative algorithm. Given a value at the ι-th iteration, v^ι, we update v by solving for $v^{\iota+1}$ in the equation below:

$$(\rho \cdot Id - L)v^{\iota+1} - v^\iota[L^* + Gv^\iota + Q] = \bar{v}$$

In each iteration, we use the Sylvester equation solver for $AX + XB = C$, where we set $A = \rho \cdot Id$, $B = L^* + Gv$, and $C = \bar{v}$. Intuitively, this means that within one iteration, we calculate how the

[32]In our model, the largest eigenvalue for $(Id-T)^{-1}$ is 1.1, and the Euclidean norm is 3.9, suggesting that the existence of the coworker network amplifies the effect of changes in the values obtainable at each firm.

value of a worker in firm jn changes due to the labor law of motion resulting from the addition of a worker in firm ik, using the current value of v^ι . The new $v^{\iota+1}$ then ensures that worker optimization is satisfied by considering the partial equilibrium force and converting the general equilibrium forces back to utils.

After obtaining the deterministic impulse value, we can directly obtain the stochastic impulse value, ω. Since all the other terms in equation (28) are known at the steady state, ω can be found by solving for the equation below:

$$(\rho \cdot Id - L + vG + Q)\omega = \bar{\omega} + vH - \eta z \omega'(z) + \frac{1}{2}\omega'(z) \tag{30}$$

3.4 Transition Dynamics

Once we have the deterministic and stochastic impulse values, we can compute the law of motion of worker distribution at each firm following the sector-specific shocks.

Proposition 3. *Given initial worker distribution n_0, the transition dynamics to the sectoral shocks $\{z_t\}$ satisfy:*

$$\frac{dn_t}{dt} = (L^* + Gv + Q)n_t + (G\omega + H)z_t \tag{31}$$

Note that all the object in equation (31) have already been obtained when solving for the impulse values. We can then compute any impulse response to a shock or to changes in the labor distribution using time iteration forward.

Given $n_0 = 0$, we can iterate forward to obtain the labor distribution deviation from the steady state

$$(Id - (L^* + Gv)\Delta_t)n_t = n_{t-1} + \Delta_t * (G\omega + H)z_t$$

3.5 Worker Welfare

After calculating the values obtainable from working in each firm and the worker distribution, we can compute the change in welfare following an aggregate shock. We denote by $\bar{V}_t = \sum_{j \in \mathcal{M}_N} \sum_{n \in \mathcal{N}} V^{jn}$ the aggregate value across all workers in the population, and write it as a function of the impulse values.

Proposition 4. *The change in worker welfare as a response to the sectoral TFP shocks can be written as:*

$$d\bar{V} = \mathbb{E}_L[\epsilon \omega^{jn} z] + Cov_N\left[\frac{\epsilon dL^{jn}}{L^{jn}}, V^{jn}\right] + Cov_N\left[\epsilon^{v^L}_{jn}, \frac{\epsilon dL^{jn}}{L^{jn}}\right] \tag{32}$$

where we denote $\epsilon^{v^L}_{ik} = \sum_{jn} L^{jn} v^{jn,ik}$.

Proof. See Appendix D.3. □

In equation (32), the first term represents the direct impact of the sectoral shocks, the second term represents the change in the aggregate value that stems from the partial-equilibrium value reallocation that results from the change in worker distribution, and the final component represents the impact from the change in value that is caused by a general equilibrium force: when the distribution of labor in the economy changes, the value obtained from each worker employed in a firm jn also changes because of the change in prices and wages, and how much it changes is given by the impulse value, $v^{jn,ik}$ for each ik.

4 Model Quantification

Our estimation procedure comprises three steps. First, we calibrate the baseline parameters related to worker preferences and production technology. Second, we present the estimating equations that map the parameters related to job choice elasticity to the data moments. Combined with another equation governing within-sector, cross firm bilateral transitions, we recover the within-sector job-switching elasticity, the job-switching rate, and the two parameters governing the influences of the coworker network on firm-level productivity belief and transition costs. Third, we turn to the steady state and use an estimating equation on the bilateral transitions across sectors to recover the two parameters dictating the impacts of coworker network on sector-level productivity belief and switching costs. We report the parameter values for our model in Table 4.

A challenge in our estimation process is the granular nature of our establishment-level data, which results in a high number of zero-value flows in labor transitions between individual establishments. This sparsity can lead to computational challenges and potentially unreliable estimates. To address this issue, we group firms into four bins within each sector according to their quality, as measured by the quartiles of AKM firm fixed effects. This method allows us to cluster establishments with similar wage premiums, which serve as a proxy for unobserved firm characteristics affecting worker compensation and mobility decisions.

By aggregating establishments into these quality-based clusters, we achieve several important objectives. We mitigate the problem of sparse transition matrices, improving the statistical power and reliability of our estimates. This approach aligns with theoretical models that emphasize the role of firm heterogeneity in worker sorting and labor market dynamics. It enables the analysis of broader patterns of worker flows between different segments of the firm quality distribution, providing insights into job ladders and labor market mobility. Moreover, it maintains consistency with our empirical analysis on the effects of coworker networks on firm choice.

4.1 Baseline Parameters

We start by determining externally baseline preference and production-related parameters. We interpret an interval $[t, t = 1)$ as one year. First, we set the discount rate $\rho = 0.05$. In addition, we set the parameter $\zeta = 0.2$, so that the correlation of taste shocks for jobs within one's own sector is roughly $1 - \zeta = 0.8$. The correlation of taste shocks for firms within the same sector is relatively high. This is because in our model firms are categorized into quality-based groups within each sector, rather than being treated as individual entities. This grouping means that distinct characteristics of individual firms within a quality group are aggregated, potentially reducing the perceived differentiation between firms from a worker's perspective. When firms are categorized into broad quality-based groups, it reduces the granularity of the choice set that workers face. Instead of considering each firm individually, workers are essentially evaluating groups of firms with similar quality levels. This aggregation can lead to a higher correlation of taste shocks because it smooths out some of the firm-specific idiosyncrasies that might otherwise differentiate worker preferences. Furthermore, we set the baseline job-switching rate $\phi = 2.3$, corresponding to around 00% of workers having the option to switch within a year pre-COVID. This value reflects the high labor market turnover rate prior to the pandemic, while leaving room for factors that might constrain job mobility for some workers, such as specialized skills, geographical limitations, or contractual obligations. Finally, we set the firm-level transition cost $\bar{\kappa} = 15$.

On the production side, we set labor share of income $1 - \gamma = 0.63$, which is relatively stable across all years in Germany. To obtain α_n, we retrieve the output data for each sector from the German Federal Statistical Office (Destatis). We then calculate the share of each sector in the aggregate output and average these shares across all years in the analysis.

We now turn to estimating the sector-and firm-level productivities, including the time-invariant firm-specific TFP and the parameters related to the OU process that governs the extent and the volatility of the sector-specific shocks. Note that we can rearrange equation (9) to obtain the sector-level TFP as a function of wages, prices, labor distribution, and the firm-level TFP:

$$\log(Z_t^n) = \log(w_t^{jn}/p_t^n) + \gamma \log(L_t^{jn}) - \log(1-\gamma) - \log(B^{jn})$$

With the normalization that the mean of logged firm-specific productivity is equal to 0 within each sector, we recover the data implied Z_t^n by matching $\log(Z_t^n)$ to the mean of a term consisting of all observables and the model parameter, γ, that has already been calibrated:

$$\log(Z_t^n) = \frac{1}{M_n} \sum_{j \in \mathcal{M}_n} \log(w_t^{jn}/p_t^n) + \gamma \log(L_t^{jn}) - \log(1-\gamma) \tag{33}$$

For each firm within sector n, we can then recover its firm-specific TFP:

$$\log(B^{jn}) = \Big[\log(w_t^{jn}/p_t^n) + \gamma \log(L_t^{jn}) - \log(1-\gamma)\Big] - \frac{1}{M_n}\big[\sum_{j \in \mathcal{M}_n} \log(w_t^{jn}/p_t^n) + \gamma \log(L_t^{jn}) - \log(1-\gamma)\big] \tag{34}$$

Now, we estimate the parameters governing the evolution of sector-level TFP. First, note that the discretized version of the sectoral shock process can be written as:

$$\log(Z_{t+1}^n) = (1 - \exp(-\eta)) \log(\tilde{Z}^n) + \exp(-\eta) \log(Z_t^n) + \delta^n \epsilon_t \tag{35}$$

where $\epsilon_t \sim N(0, \frac{1-\exp(-2\eta)}{2\eta})$. Thus, we can pool across all sectors n and regression $\log(Z_{t+1}^n)$ on

$\log(Z_t^n)$, while including the sector-fixed effects:

$$\log(Z_{t+1}^n) = a^n + \beta \log(Z_t^n) + \sigma$$

We can then recover the parameters from the coefficient estimates of this regression

$$\eta = -\log(\hat{\beta}), \quad \tilde{Z}^n = \exp\big(\frac{\hat{\alpha}^n}{1 - \exp(-\eta)}\big)$$

Finally, we can back out the sector -specific volatility, δ^n, given that the variance of the residuals for each n will be equal to $(\delta^n)^2 \frac{(1-\exp(-2\eta))}{2\eta}$.

Our estimation results suggest that Agriculture and Mining have the lowest sector-level productivity and the lowest variance in firm quality across different AKM firm fixed effects quartiles. Service sectors generally have higher sector-level TFP, with Accommodation and Arts featuring the highest productivity among them. On the other hand, Utilities, Water Supply, and Waste Management exhibit both high sector-wide productivity levels and the highest variance in firm quality. The extent of autoregression in sector-level productivity is comparable across different sectors, with the manufacturing sector having the highest and the Information and Professional sectors having the lowest. The estimated values for sector-level productivity can be found in Table E1.

4.2 Within-sector Elasticity, and Cross-firm Coworker Network

We first estimate parameters related to job-switching within sectors and across firms. These parameters include the within-sector job switching elasticity ($\nu\zeta$), and the parameters governing how important coworker networks are for perceived firm-level TFP (β_1) and for costs associated with cross-firm transitions (α_1). Our estimation approach combines two estimating equations, which can be thought of as linear regressions. We employ an iterative algorithm that updates in a simple, intuitive way and delivers fast convergence. The first equation builds upon the method introduced by Artuç, Chaudhuri and McLaren (2010) (henceforth ACM) and involves an analogous estimating equation that relates current job flows to wage differences and expected future flows. The second equation takes advantage of the symmetric structure in the cross-flow equations and relates bilateral job flows to coworker networks. We now elaborate on these two equations and the iterative algorithm.

Equation Comparing Cross-firm Flows with Job Stayers Our first estimating equation resembles the one in ACM, but differs from ACM in four aspects. First, our model operates in continuous time, whereas the estimating equation in ACM relates the current-period and the next-period flows. Second, our model assumes agents have log utility, leading us to replace the absolute wage differential in ACM with the logged wage differential, paralleling our reduced-form specification and emphasizing proportional changes in wages. Third, instead of using a multinomial logit, our model features a nested logit structure. This approach requires us to separately identify the overall job-switching elasticity from the correlation of taste shocks within each sector. Most importantly, we emphasize the importance of coworker networks on job-switching decisions, consequently requiring the inclusion of coworker network variables in our estimating equations to account for their influence. The estimating equation is:

$$
\begin{aligned}
&(\rho-1)\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}}+\log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}}+\frac{\beta_1(l_t^{n,jn}-l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn}+\frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn}-l_{t-1}^{rn,jn})\bar{\kappa}^{jn,rn}= \\
&\frac{1}{\nu\zeta}\Big[\log\frac{w_t^{rn}}{w_t^{jn}}-\frac{\rho}{\rho+\phi}\log B^{rn}\Big]-\frac{\phi}{\zeta}\log\frac{\mu_t^{rn,n}}{\mu_t^{jn,n}}-\phi\log\frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}}-\frac{\phi\beta_0(l_t^{n,rn}-l_t^{n,jn})}{(\rho+\phi)\nu\zeta}\Big(\bar{z}_t-\log(Z_t^n)\Big) \qquad (36) \\
&+\frac{\rho\beta_1 l_t^{n,jn}}{(\rho+\phi)\nu\zeta}\log B^{rn}-\frac{\rho}{\nu\zeta}\bar{\kappa}^{jn,rn}+\frac{\rho\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa}^{jn,rn}+\epsilon_t
\end{aligned}
$$

Equation (36) illustrates how within-sector, cross-firm job flows provide insights into the expected values of employment at various destination firms. These values are influenced by future wages, the option values of subsequent job switches, coworker network compositions at those firms, and future cross-firm flows. We impose the assumption that the transition cost at the firm level within one's own firm, $\bar{\kappa}^{jn,jn}$, is equal to 0 for every firm in the economy. The derivation of this equation is detailed in Appendix E.2.

This equation allows us to recover the within-sector job-switching elasticity $\frac{1}{\nu\zeta}$ and the rate of job-switching rate ϕ by regressing the difference between the relative size of flows from the same origin towards two distinct firms within the same sector and the expected changes in the future relative size of the same flows, after adjusting for the influence from the coworker networks, on two key factors: the relative logged wage differential and the relative fraction of job stayers. This regression also controls for the relative fraction of sections stayers, as well as the terms characterizing the influence of coworker networks.

The term on the left-hand side of the equation, $\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}}-\log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}}$, is an approximation to the instantaneous change in the cross-firm flows, and characterizes the relative difference in the expected values of being employed in the two destination firms of interest. It is analogous to the discrete-time counterpart of the estimating equation, which represents the discounted next-period value function, $V_{t+1}^{rn}/V_{t+1}^{jn}$, through the relative next-period flows $\mu_{t+1}^{jn,rn}/\mu_{t+1}^{jn,jn}$ in ACM.[33] If the instantaneous change in value (or flow) from jn to rn is larger, then the expected continuation value of being employed in rn is larger, which also lead to a higher level of current-period flow from jn to rn relative to the fraction of workers that stay in jn. However, due to coworker network effects, relative flows across periods can be influenced by differences in coworker compositions, not just the inherent values of employment at the two firms. To reflect actual changes in obtainable value at the two firms, we adjust this difference by the coworker network differences over time, $\frac{\beta_1(l_t^{n,jn}-l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn}+\frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn}-l_{t-1}^{rn,jn})\bar{\kappa}^{jn,rn}$.

The terms on the right-hand side of the equations characterize the relative attractiveness of the

[33]We approximate $\mathbb{E}[d\mu_t^{jn,rn|n}]$ and $\mathbb{E}[d\mu_t^{jn,jn|n}]$ using the central differences formula. Specifically, we set $\mathbb{E}[\mu_t^{jn,rn|n}]=(\mu_{t+1}^{jn,rn|n}-\mu_{t-1}^{jn,rn|n})/2$. The approximated expression for the estimating equation still involves $\mu_{t+1}^{jn,rn}$ and $\mu_{t+1}^{jn,jn}$.

two destination firms at the present time. The first term, $\log \frac{w_t^{rn}}{w_t^{jn}} - \frac{\rho}{\rho+\phi} \log B^{rn}$, represents the perceived logged wage differential at the two destination firms.[34] Its impact on job flows depends on both the elasticity of job switching and the correlation of taste shocks for firms within the same sector. As the job-switching elasticity, $\frac{1}{\nu}$, increases, individuals become less focused on the idiosyncratic, non-monetary factors, basing their decisions more on the pecuniary aspects of job compensation. Additionally, when the correlation of taste shocks, $1 - \zeta$, rises, employees perceive jobs as having more similar unobserved attributes, making them more likely to be influenced by observable factors. Consequently, they become more sensitive to wage disparities in both cases.

Intuitively, the second and the third terms, $\log \frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}}$ and $\log \frac{\mu_t^{rn,n}}{\mu_t^{jn,n}}$, enter into the relative option values of job-switching when currently employed at a certain firm. The second term says that the greater the probability of remaining in sector n from a firm rn, the lower the value of having the option to move from firm rn overall. Moreover, as the correlation of the taste shocks for firms within the sector n, $1 - \zeta$, increases, the more similar the other alternatives within that sector appear to the worker and the more likely the worker to switch to another firm within the sector if the utility derived from working in her current firm decreases.[35] This would translate into a higher option value of moving. Under the same reasoning, the third term indicates that the option value of staying at a firm decreases with the fraction of job stayers at rn conditional on staying with the sector n. Moreover, both terms increase with the possibility of being able to switch jobs increases, as the option value is higher for all firms within the economy when moving becomes more likely.

The remaining terms illustrate how networks of coworkers influence the movement of workers between firms in the same sector. The expression $\frac{\phi\beta_0(l_t^{n,rn} - l_t^{n,jn})}{\nu\zeta} \left(\bar{z} - \log(Z_t^n)\right)$ shows how coworker networks affect workers' perceptions of sector-wide productivity and their likelihood of staying in their current sector. As the proportion of workers in firm rn who previously worked in sector n increases compared to those in firm jn, workers gain a more accurate understanding of the sector's overall productivity. This improved understanding allows workers to make better future decisions regarding sector-switching that maximize their utility, and consequently increases the option value of moving to firm rn.

Coworker networks not only influence beliefs about sector-specific productivity but also affect how workers respond to firm-specific productivity levels. Our model assumes that workers' perception of their own firm's productivity is accurate and independent of the fraction of job stayers within the firm. Consequently, the firm-level coworker network composition does not directly modify the option value of switching to a particular destination firm. However, the network composition has a

[34]Unlike ACM or other existing works that estimate job-switching elasticity by regressing relative flows on the logged wage differential ($\log \frac{w_t^{rn}}{w_t^{jn}}$), our estimating equation adjusts for the mis-perception of the destination-firm wage without coworker influence, which is equal to $\frac{\rho}{\rho+\phi} \log B^{rn}$. This approach is driven by our model's assumption that coworker networks can affect one's elasticity to wage gain. Therefore, to estimate the elasticity of job-switching with respect to wage, we need to use the perceived wages as opposed to the actual wages.

[35]This is relative to switching to a firm outside of the sector.

more direct impact on the ratio of job switchers to job stayers for a given pair of origin and destination firms. This is because it directly influences the perceived Total Factor Productivity (TFP) of the destination firm. The term $\frac{\rho\beta_1 l_t^{n,jn}}{(\rho+\phi)\nu\zeta}\log B^{rn}$ captures this effect. Here, $l_t^{n,jn}$ represents the proportion of workers in firm jn that has been employed within sector n, and B^{rn} denotes the productivity level of firm rn. As the proportion of workers in firm jn from sector n increases, employees there can obtain more information of the firm-specific TFP at each firm within sector n, and therefore become more aware of and more responsive to the firm's specific productivity level.

Lastly, coworker networks not only change how responsive job switching is to productivity differences but also affect the overall level of job switching. This can be seen in the terms, $-\frac{\rho}{\nu\zeta}\bar{\kappa}^{jn,rn} + \frac{\rho\alpha_1}{\nu\zeta} l_t^{rn,jn}\bar{\kappa}^{jn,rn}$. While $\bar{\kappa}^{jn,rn}$ represents the inherent cost of changing jobs, this cost can be influenced by the proportion of one's coworkers. As the fraction of workers previously employed in firm rn increases, it becomes easier for workers in firm jn to switch to rn, regardless of the productivity or compensation differences between the two firms.

Equation Comparing Bilateral Flows across Firms within a Sector Estimating job choice elasticity and job switching rate in equation (36) requires knowing the terms that characterize the importance of firm-level coworker networks. We therefore estimate the parameters governing firm-level influences of coworker network jointly by taking advantage of the symmetry in our bilateral transition across firms equations. We write:

$$\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log\frac{\mu_t^{rn,jn|n}}{\mu_t^{rn,rn|n}} = \frac{\beta_1(l_t^{n,jn}\log B^{rn} - l_t^{n,rn}\log B^{jn})}{\nu\zeta(\rho+\phi)} - \frac{1}{\nu\zeta(\rho+\phi)}(\log B^{rn} + \log B^{jn})$$
$$- \frac{1}{\nu\zeta}(\bar{\kappa}^{jn,rn} + \bar{\kappa}^{rn,jn}) + \frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn}\bar{\kappa}^{jn,rn} + l_t^{jn,rn}\bar{\kappa}^{rn,jn})$$

We now impose some additional assumptions on the firm-level transition costs that are intuitive and can reduce the dimensionality of the parameter space.

Assumption 5. *The firm-level costs associated with job switching is constant for all workers that move to a across firm groups. Transitioning within one's firm group incurs a zero firm-level transition cost.*

$$\bar{\kappa}^{jn,ik} = \begin{cases} \bar{\kappa} & \text{if } j \neq k \\ 0 & \text{if } j = k \end{cases}$$

Assumption (5) allows up to maintain parsimony and tractability in the model. While transitions from low-quality to high-quality firm are typically associated with a positive costs due to the necessity of skill-upgrading or more intensive networking, moving from high-quality to low-quality firms can be costly as well due to several reasons. Firstly, workers moving from high to low-quality firms often face psychological costs, including potential loss of prestige and reduced job satisfaction. Secondly, there may be tangible opportunity costs, such as forfeiting advanced training opportunities or highpowered incentive structures common in high-quality firms. Thirdly, workers might need to adapt to less sophisticated technologies or processes, requiring time and effort to adjust their working methods. Additionally, there could be signaling costs in the labor market, where such a move might be perceived negatively by future employers. Finally, workers may suffer human capital depreciation. With this assumption, we can then write the equation consisting of bilateral within-sector, cross-firm flows as:

$$\begin{aligned} &\log \frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log \frac{\mu_t^{rn,jn|n}}{\mu_t^{rn,rn|n}} + \frac{1}{\nu\zeta(\rho+\phi)}(\log B^{rn} + \log B^{jn}) \\ =&\frac{\beta_1}{\nu\zeta(\rho+\phi)}(l_t^{n,jn}\log B^{rn} + l_t^{n,rn}\log B^{jn}) + \frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn} + l_t^{jn,rn})\bar{\kappa} - \frac{2}{\nu\zeta}\bar{\kappa} \end{aligned} \tag{37}$$

This assumption also simplifies equation (36):

$$\begin{aligned} &(\rho-1)\log \frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log \frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}} + \frac{\phi}{\zeta}\log \frac{\mu_t^{rn,n}}{\mu_t^{jn,n}} + \phi \log \frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}} \\ &+ \frac{\beta_1(l_t^{n,jn} - l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn} + \frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn} - l_{t-1}^{rn,jn})\bar{\kappa} - \frac{\rho\beta_1 l_t^{n,jn}}{(\rho+\phi)\nu\zeta}\log B^{rn} + \frac{\rho}{\nu\zeta}\bar{\kappa} - \frac{\rho\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa} = \\ &\frac{1}{\nu\zeta}\Big[\log \frac{w_t^{rn}}{w_t^{jn}} - \frac{\rho}{\rho+\phi}\log B^{rn}\Big] - \frac{\phi\beta_0(l_t^{n,rn} - l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\Big(\bar{z}_t - \log(Z_t^n)\Big) + \epsilon_t \end{aligned} \tag{38}$$

The Iterative Algorithm We recover the model parameters through an iterative algorithm that combines equations (37) and (38). First, we evaluate firm-level coworker networks using equation (37). Intuitively, the responsiveness of bilateral flows between two firms to firm-level productivity depends on the structure of these coworker networks. Thus, we identify the impact of coworker networks by relating the sum of flows between firms to the sectoral composition of coworkers, as well as the interaction between the sectoral coworker composition and the logged firm-level productivity in those firms. With estimates of the firm-level coworker network parameters, α_1 and β_1, in hand, we can control for coworker network-adjusted transition costs. This, in turn, allows us to identify firm-level job-switching elasticity by regressing the logged job-switching rate on the logged wage differential between the destination and origin firms.

The iterative algorithm proceeds as follows: We begin by guessing an initial value for $\nu\zeta$. Using this guess, we calculate the term $\frac{1}{\nu\zeta(\rho+\phi)}(\log B^{rn} + \log B^{jn})$. This allows us to obtain the left-hand-side object in equation (37). By regressing this on the sum of coworker networks at both firms and coworker-adjusted firm-level productivity, we estimate α_1 and β_1, which capture the influence of coworker networks at each origin firm. With these estimates, we can obtain all objects on the left-hand side of equation (38). Regressing these left-hand-side terms on the relative logged wage differential between the two firms yields a new estimate of the firm-level elasticity, $\nu\zeta$. We then compare this value with the initial guess and iterate until convergence. A more detailed description of this estimation procedure is provided in Appendix E.4.

Discussion on Estimated Values Table E4 presents the coefficient estimates for the relevant terms in equation (36). We estimate a job-switching elasticity of 0.38 across all firms. Our estimated job-switching elasticity aligns well with recent findings in the monopsony literature, where elasticities often range from 0.1 to 0.5 in concentrated labor markets or low-wage sectors (Webber 2015, Bachmann and Frings 2017, Gottfries and Jarosch 2023, Dodini et al. 2023, Berger et al. 2023). Our sector-switching elasticity estimates are derived from an analysis aggregated across all locations, focusing exclusively on transitions between industries, without accounting for geographic or occupational mobility. In contrast, previous studies often incorporate additional channels, such as geographic or occupational mobility (e.g., Artuç, Chaudhuri, and McLaren, 2010; Caliendo, Dvorkin, and Parro, 2019), or focus solely on occupation-switching (e.g., Traiberman, 2019).[36] Without the additional frictions introduced by geography or occupation, workers in our model respond more elastically to sector-specific wage differentials, which may explain the higher elasticity estimate. Furthermore, our model incorporates an additional mechanism: the coworker network. Since we attribute part of job-switching behavior to more accurate beliefs about firm-level productivity—rather than solely observed wage differences—this coworker mechanism may result in a lower estimate of job-switching elasticity compared to models that assume perfect information and decisions based only on actual wages. Overall, our estimates are in line with those of Caliendo, Dvorkin, and Parro (2019), who estimate an annual elasticity of labor market transitions of 0.50.[37] The firm-level job-switching cost, $\bar{\kappa}$, is estimated at 11.91.

The coworker-related parameters, α_1 and β_1, are novel contributions and have not been previously estimated in the literature. To understand their impact on job-switching elasticity and rates, we conduct a series of comparative analyses by manually setting α_1 and/or β_1 to zero and examining the resulting coefficient estimates. In our preferred specification, which allows the coworker network to influence both the perceived TFP of the destination firm and the transition costs associated with moving to that firm, we estimate α_1 to be 7.05 and β_1 to be 1.16. Shutting down the influence of coworkers on firm-level adjustment costs leads to a slight overestimation of job-switching elasticity and an underestimation of baseline firm-level job-switching costs. This illustrates that, without considering the role of coworkers in reducing adjustment costs, the model may the entirety of observed worker flows to wage differentials.

[36] Additionally, some studies, such as Artuç, Chaudhuri, and McLaren (2010), estimate semi-elasticity rather than elasticity, due to their assumption of linear utility. For instance, they estimate an inverse semi-elasticity of 1.88 at an annual frequency.

[37] Caliendo, Dvorkin, and Parro (2019) estimate elasticity at a quarterly level in their baseline model but note that the inverse elasticity at an annual frequency would be 2.02.

4.3 Cross-sector Coworker Network

Our final step is to estimate the fundamentals related to job switching costs across firms and across sectors. Now, we have obtain estimates of the job-switching elasticity ν and parameters representing the correlation of taste shocks for firms within the same sector ζ. Using equations (19) and (20), we can write:[38]

$$\log \frac{\mu_t^{jn,k}}{\mu_t^{jn,n}} + \log \frac{\mu_t^{ik,n}}{\mu_t^{ik,k}} = -\zeta(S_t^{jn,k} - S_t^{ik,k}) - \zeta(S_t^{jn,n} - S_t^{ik,n})$$
$$+ \frac{\beta_0}{\nu(\rho+\phi)}\left[(l_t^{k,jn} - l_t^{k,ik})\log(Z_t^k) - (l_t^{n,jn} - l_t^{n,ik})\log(Z_t^n)\right] + \frac{\alpha_0}{\nu}\left[l^{k,jn} + l^{n,ik}\right]\bar{\kappa}^{n,k} \tag{39}$$

Similar to the firm-level job-switching decisions, we now impose an additional assumption on the firm-level transition costs to reduce the number of parameter values to be estimated.

Assumption 6. *The sector-level costs associated with job switching is zero for own-sector transition. It is symmetric for cross-sector transitions.*

$$\bar{\kappa}^{n,k} = \begin{cases} \bar{\kappa}^{k,n} & \text{if } n \neq k \\ 0 & \text{if } n = k \end{cases}$$

Equation (39) needs to be examined at the steady state since it involves the inclusive value of moving into each possible destination sector. Given that the sector-level transition costs are allowed to vary across sector pairs, the sector-level flows can no longer be represented through a linear regression of model observables. We therefore use Generalized Methods of Moments, by matching the model-implied and data-implied differences in inclusive values of being employed in each sector, $(S_t^{jn,k} - S_{t^{ik,k}}) - (S_t^{jn,n} - S_t^{ik,n})$, across all combinations of origin firm pairs. A detailed description can be found in Appendix E.4. We estimate $\alpha_0 = 0.06$ and $\beta_0 = 4.17$, suggesting that coworker network plays an significant role in influencing workers' beliefs on the sector component of TFP. The matrix of cross-sector transition costs can be found in Table E5. Overall, we estimate that it is the most difficult to transition from Trade, Transportation, and Storage, as well as Accommodation, Administration, Arts, and Other Services to the other sectors.

Non-targeted Moments We validate our parameter estimates by comparing non-targeted model moments with their counterparts in the data. Since our calculation of the impulse responses to sectoral shocks relies on local perturbations around the steady state, it is crucial that these moments align with what we observe in the data. In Tables E6 and E7, we demonstrate that the model-implied labor distribution and sectoral transitions closely match the corresponding data moments. The correlation between the steady-state labor distribution across firms in the data and in the model is 0.9, and the

[38] See Appendix E.3 for more details.

mean of the absolute difference is 0.001. The absolute differences between the sector-level transition probabilities in the data and implied by the model are on average only 0.02, with a median being 0.001.

Table 4: Parameter Values

Parameter	Value	Statistic	Related Moment
ρ	0.05	Value	Discount rate
ϕ	2.3	Value	Job-Switching Rate
ζ	0.2	Value	Correlation of taste shocks within each sector
$\bar{\kappa}$	15.0	Value	Levels of cross-firm flows by firm pair
γ	0.37	Value	Labor Share of Income
α^n	[0.01, 0.29]	Range	Consumption share of sectoral goods
η	0.14	Value	Autocorrelation of sector-specific productivity process
$\log(B)^{jn}$	[-1.50, 1.37]	Range	Mean of firm-specific wage and production
$\log(Z^n)$	[3.10, 4.33]	Range	Level of sector-specific productivity process
δ^n	[0.03, 0.08]	Range	Variance of sector-specific productivity process
ν	2.63	Value	Elasticities of cross-firm flows w.r.t. wage
$\bar{\kappa}^{n,k}$	[1.28, 12.36]	Range	Levels of cross-sector flows by sector pair
α_0	0.06	Value	Levels of cross-sector flows shared across all sectors
α_1	7.05	Value	Levels of cross-firm flows
β_0	4.17	Value	Elasticities of cross-sector flows w.r.t. TFP
β_1	1.16	Value	Elasticities of cross-firm flows w.r.t. TFP

Notes: The model is calibrated at yearly frequency. "Sector-specific" productivity process refers to the value backed out from the level wage, price, and labor distribution of each firm firm that belongs to a certain sector, according to equation (33).

4.4 Identifying the COVID shock by Sector

Having established our estimation framework, we turn to the context of our study: the impact of shock similar to COVID on sectoral productions, to see how coworker networks matter in an environment with a high degree of reallocation, and where countries have policies with different implications for the labor mobility across sectors.

We model the impacts of COVID on the German labor market as sector-specific productivity shocks, which provides a tractable framework to analyze its heterogeneous impacts across the economy. This approach aligns with a growing body of literature in economics that views the pandemic primarily as a supply-side disruption.[39] Moreover, this approach allows for the incorporation of the pandemic's differential impact across sectors, as observed in the disproportionate effects on service industries requiring face-to-face interactions compared to those more amenable to remote work. Finally, while changes in demand, such as shifts in consumer behavior or reductions in service usage, undoubtedly played a role, both supply disruption and demand fluctuations ultimately influence revenue productivity, as firms adjust their operations in response to TFP changes.Given our focus on sectoral changes and reallocation, a TFP framework effectively captures COVID's effects on economic restructuring

Due to limitations in data availability on sectoral Total Factor Productivity (TFP) changes in Germany during the COVID-19 pandemic, we approximate these changes using sectoral TFP data from the United States. This approach can be justified for several reasons. First, in our model, it is the relative size of TFP shocks across sectors that is critical, rather than the absolute changes in productivity levels. The proportional impact of the pandemic on different sectors is likely to be similar between the U.S. and Germany. Second, the COVID-19 pandemic was a global shock that affected economies worldwide in similar ways—through supply chain disruptions, changes in consumer demand, and lockdown measures. Therefore, sectoral TFP changes observed in the U.S. are likely to reflect broader trends that also occurred in Germany.

We approximate the COVID-19 productivity shock using data from the Bureau of Economic Analysis (BEA) Integrated Industry-Level Production Account (ILPA), commonly referred to as KLEMS data. The KLEMS framework provides detailed estimates of the sources of economic growth at the industry level by decomposing output growth into different sources of contributions.[40] We take the variables representing the contribution of TFP to production in years 2019 and 2020.[41]

To align the U.S. data with German industry classifications, we construct a crosswalk that maps sectors from the North American Industry Classification System (NAICS) to the Statistical Classification of Economic Activities in the European Community (NACE) sectors. We calculate the percentage change in TFP for each sector as well as the overall economy from 2019 to 2020, attributing the observed changes to the impact of COVID-19, given that the pandemic began abruptly at the start of 2020.

To relate the TFP changes to our framework, we model the COVID shock as a common underlying shock z_t that affects all sectors, while allowing for sector-specific responses through ϵ^n.[42] This formu-

[39] For instance, Guerrieri et al. (2022) model the pandemic as sector-specific supply shocks that can trigger changes in aggregate demand larger than the shocks themselves. Similarly, Baqaee and Farhi (2022) use a multi-sector model to show how COVID-19 shocks propagate through production networks, demonstrating that sector-specific productivity shocks can have significant macroeconomic effects. This modeling strategy captures the essence of how COVID-19 affected economies: through disruptions to labor supply, changes in work practices, and interruptions to supply chains, all of which can be conceptualized as negative shocks to sectoral productivity.

[40] Specifically, it decomposes growth into contributions from capital (K), labor (L), energy (E), materials (M), and services (S), along with total factor productivity.

[41] Since, we assume that the . Moreover, we examined the TFP changes by sector from 2017 to 2020 in the KLEMS dataset, and the directions and magnitudes are comparable to the case when we calculate changes from 2019 to 2020.

[42] We set $\epsilon^n = \log(Z^n_{post}/Z^n_{pre})/\log(Z_{post}/Z_{pre})$.

lation captures the global nature of COVID as a systemic event, while reflecting sectoral heterogeneity in the magnitude and direction of the impact. The common shock z_t represents a shared economic disturbance, while ϵ^n adjusts the sectoral sensitivity to this shock, with $\epsilon^n > 0$ indicating sectors that benefited and $\epsilon^n < 0$ indicating sectors that suffered. This approach is justified as it simplifies the modeling of a complex global event by using a unified shock structure, yet allows for differential sectoral outcomes, aligning with empirical evidence showing the varying effects of COVID across industries. Furthermore, by focusing on the relative shock impact, this method captures the dynamics of resource reallocation and sectoral competitiveness following the pandemic.

Table E8 presents the magnitude of the productivity shock by sector. Despite negatively impacting the economy overall, COVID-19 influenced each sector in heterogeneous ways. As expected, manufacturing, trade, finance, and all service sectors experienced negative impacts due to the pandemic. On the other hand, agriculture, utilities, construction, and IT benefited from it. One notable pattern is that sectors with lower baseline productivity tended to experience productivity gains because of COVID-19, while sectors with higher baseline productivity tended to experience productivity losses.

5 Evaluating Policies that Limit Mobility

To highlight the importance of the coworker mechanism, we evaluate a policy that affect the incentives of workers and firms to relocate across regions. It is ex-ante unclear how increased labor movement matters in the aggregate as it engenders two forces in opposite directions. On one hand, an elevated level of labor movement can increase awareness of opportunities and reduces transition costs, thereby shifting the labor distribution into sectors that are experiencing a positive shock. On the other hand, labor movement towards high-productivity sectors increases competition within those sectors, which reduces the wage obtainable if employed in those sectors because of diminishing returns to labor. Therefore, it is crucial that we turn to our quantitative framework to evaluate the relative magnitudes of the reallocation effect and wage effect from changes in labor movement overall, as well as the distributional impacts of shocks across different sectors.

A number of real-world policies can influence labor flows across sectors, either in terms of speed or magnitude. Examples include education and training programs, labor market information systems, unemployment insurance, and employment protection legislation. Furthermore, immigration, trade, and industrial policies, by changing the relative ease or payoff associated with transitioning into certain sectors, could also influence labor supply decisions. In this paper, we focus on evaluating the implications of policies that reduce labor mobility by tying workers to their current employers, such as short-term work arrangements.

5.1 Maintaining Worker-Employer Ties

Germany strengthened its furlough schemes during COVID-19. The Kurzarbeit system, which provided partial wage subsidies to employers to retain workers on reduced hours, effectively preserved existing employment relationships and limited job turnover. This approach maintained workforce stability but potentially hindered labor reallocation across sectors. In contrast, other countries, including the US, relied more heavily on subsidies provided directly to workers and firms, which severed employer-employee ties and theoretically allowed for greater labor mobility. Maintaining worker-employer ties during the pandemic can both restrict worker movement into the growing sectors and lead to a wage increase in those sectors because of limitations in labor supply. We examine the strengths of the wage effect vs. the reallocation effect in our model, and compare the cases with vs. without the coworker network.

Before assessing the impact of policies that limit labor mobility, we first compare wage responses in scenarios with and without coworker networks in response to a productivity shock similar to COVID-19. As shown by the solid black lines in Panels (A) and (B) of Figure 3, the shape and peak of impulse responses differ significantly between models with and without coworker networks. When coworker networks are included, labor distribution adjusts more gradually and persistently to a one-time productivity shock. Specifically, labor reallocation extends over time, with shifts in response to the COVID shock becoming more pronounced by 2030 compared to 2022. In contrast, the model without coworker networks predicts much smaller deviations in labor distribution from pre-COVID levels.[43]

What are the implications of policies that limit labor mobility? We now examine the effects of such policies by comparing high- and low-mobility scenarios in both models, with and without coworker networks. We conduct a counterfactual policy analysis by reducing the job-switching rate from 2.3 to 0.7. Setting $\phi = 0.7$ implies that only about 50% of workers can switch jobs within a year, compared to 90% in the unrestricted case.

In the baseline model with coworker influence, reducing job mobility confines workers to their current sectors, limiting their ability to shift toward sectors positively affected by the shock. As shown in Panel (C) of Figure 3, the reallocation effect is negative overall in both high- and low-mobility cases with coworker networks, as workers tend to move toward sectors positively impacted by COVID-19, which generally have lower baseline productivity levels. However, the percentage deviation from the steady-state total wage bill due to labor reallocation is smaller in high-mobility scenarios compared to low mobility, with the reallocation effect differing by a modest maximum of 0.09 basis points.

Despite reduced labor mobility, wages increase, as indicated by the dashed gray line in Panel (A) of Figure 3. This is because the general-equilibrium effects on wages outweigh the partial-equilibrium effects of labor reallocation when mobility declines. With limited movement into positively shocked sectors, wages in these sectors remain elevated due to labor supply constraints. However, this comes at the cost of a slight increase in wage inequality. Panel (E) of Figure 3 shows the standard deviation of wages across workers over the transition period, highlighting a widening disparity in the coworker network case.

In contrast, both the wage and reallocation effects from adjusting labor mobility by changing the

[43]This pattern is further illustrated in Figure F2, where sectors positively impacted by COVID's productivity shock show positive deviations in labor distribution, while negatively impacted sectors experience declines.

job-finding rate, ϕ, are significantly reduced in models without coworker networks. As shown in the dashed gray line in Panel (A) of Figure 3, total wage bills remain largely unchanged between high- and low-mobility cases, and the gains from reallocation are minimal, with a maximum percentage deviation from the steady state of only 0.0003. This suggests that implementing a furlough scheme in response to the COVID-19 productivity shock is more effective when considering the externalities generated by coworker networks, especially in the long run.

Table 5: Welfare Impact of productivity shock (% deviation from s.s.)

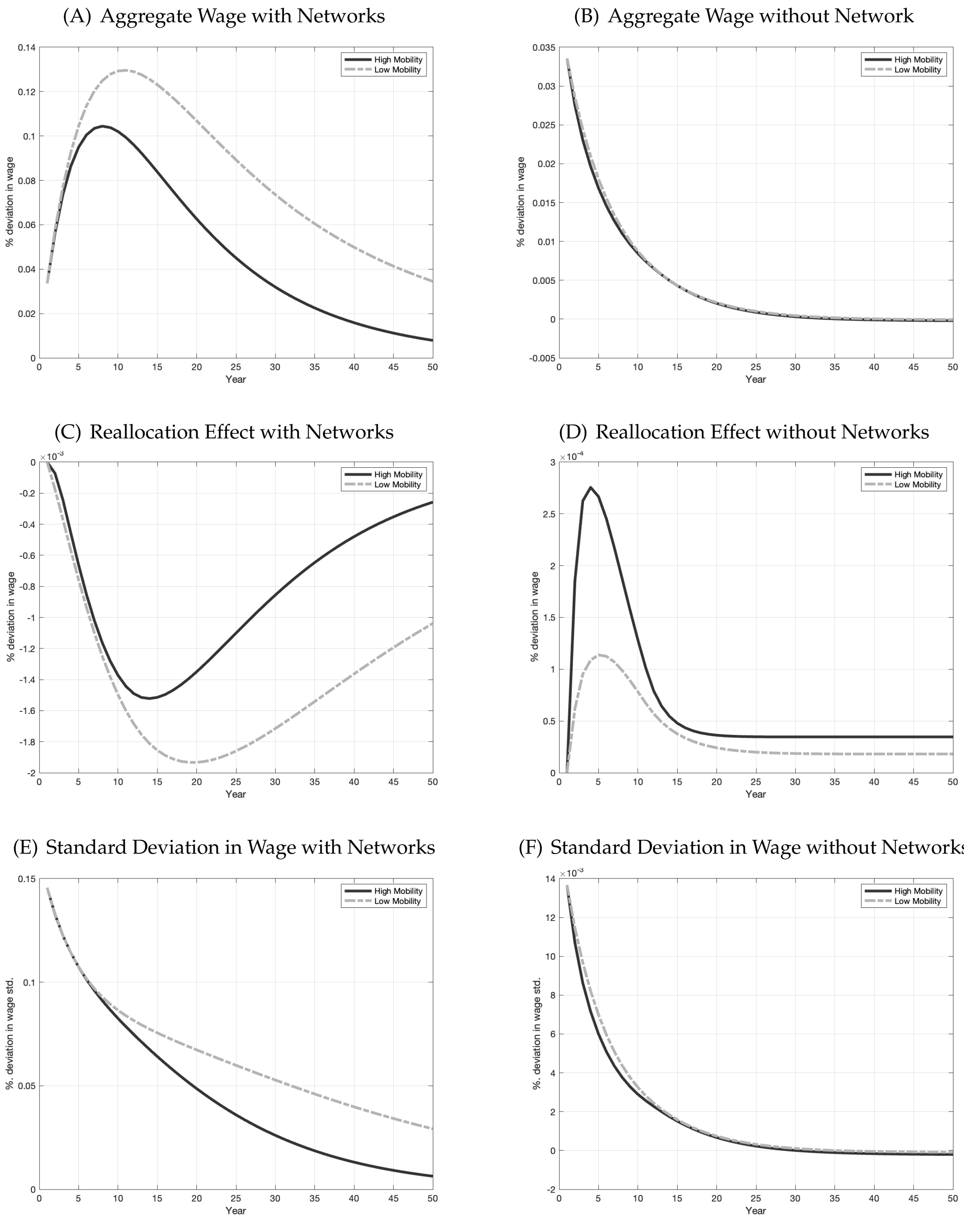
	Mechanism			
	Productivity	Reallocation	Wage	Total
Coworker Network (2022)	-0.0042	-0.0023	0.1827	0.1762
Coworker Network (2030)	-0.0004	-0.0055	0.3241	0.3182
No Network (2022)	-0.0040	0.0007	0.0005	-0.0028
No Network (2030)	-0.0004	0.0003	0.0009	0.0007

Notes: Table decomposes welfare changes in the model with coworker network vs. without coworker network.

Finally, Table 5 decomposes the percentage deviation from pre-COVID welfare into three components: the contribution from the productivity shock itself, the partial-equilibrium effect of changes in labor distribution, and the general-equilibrium effect from changes in wages (and prices) at each firm. Welfare increases by 0.177% in 2022 and by 31.8% in 2030 due to the COVID-induced productivity shock. The increase in welfare primarily comes from the general-equilibrium change in wages brought about by labor shifts. As workers move towards sectors with positive COVID productivity shocks—sectors that tend to have lower initial productivity—labor employed in negatively impacted but previously higher-productivity firms decreases. Given decreasing returns to scale, this reduction in competition boosts wages at these high-productivity firms, enhancing the welfare of workers who remain in these sectors. The magnitude of this channel is substantial because employment in these high-productivity sectors was initially large.

Failing to account for coworker networks, however, leads to an overly pessimistic assessment of welfare changes. In a model without coworker networks, aggregate welfare decreases by 0.003% in 2022 and increases by only 0.001% in 2030. Moreover, while both the partial-equilibrium reallocation effect and the general-equilibrium wage effects remain positive, they are much smaller in magnitude. Without coworker networks, workers are subject to a higher moving cost when attempting to move to other sectors. They are therefore more tied to their current jobs. Although this prevents excessive reallocation away from higher-wage sectors, it also hinders workers from moving to sectors that are growing due to the COVID shock. This reduced mobility dampens the general-equilibrium welfare gains that could have been achieved through redirecting labor supply to sectors where it is most needed.

Figure 3: Wage Responses under Coworker Influence vs. No Coworker Influence



Note: Figure plots wage responses to the productivity shock similar to the one brought about by COVID-19, in the baseline model. Panel (A) plots deviation of aggregate wage from the pre-COVID level when assuming the existence of coworker network, and Panel (B) plots deviation of aggregate wage from the pre-COVID level without coworker network. Panel (C) and (D) plot the fraction of the change in aggregate wage that is caused by labor reallocation across sectors with and without coworker networks, respectively. Panel (E) and (F) plot the change in the standard deviation of wage from the steady-state level with and without coworker networks, respectively. The solid black line represents the implied responses from our model with $\phi = 2.3$. The dashed gray line represents the implied responses in a model with $\phi = 0.7$.

6 Conclusion

Using exogenous changes in the composition of current coworkers' past sector of employment through both differences in the current-year and the non-current-year coworker shares and coworker deaths or retirements, we demonstrate that coworker networks can significantly influence an individual's firm and sector-choice decisions. These influences manifest in three aspects. First, having more coworkers from a specific sector increases the likelihood of moving into that sector on average. Second, coworker networks enhance the responsiveness of sectoral choice decisions to wage differentials between the origin and the destination sectors. Third, the impact extends to firm choices: conditional on moving into a destination sector, workers with more coworkers from that sector tend to move into higher-quality firms and remain in their new jobs for longer time. These findings collectively underscore the substantial role that coworker networks play in shaping workers' job choice decisions and calls for endogenizing the role of coworkers in sectoral choice models.

We interpret quantitatively the importance of coworker networks for sectoral shock propagation in the aggregate through the lens of a model of job choices under coworker influences. In the model, both the perceived TFP of and the adjustment costs to a destination sector are functions of the share of coworkers within a firm that were last employed in that sector. We identify the parameters related to the coworker network off of asymmetry in bilateral labor flows for a certain sector pair. Our model suggests an increase in average wage and welfare because of productivity shocks brought about by COVID, primarily because of changes in sectoral wages that accompany labor reallocation. Limiting labor mobility to some extents can be welfare enhancing.

Our findings open up several avenues for future research. One promising direction is to broaden the scope of social networks and examine their influence on individuals' labor supply decisions, particularly in the context of sectoral reallocation and the propagation of sector-specific shocks. While our study focused on a specific form of coworker networks—the composition of past sectoral employment for workers at their current job—to better identify causal effects and quantify the coworker mechanism, exploring alternative definitions could yield valuable insights. For instance, investigating the impact of former coworkers' previous or current sectors of employment and comparing their quantitative relevance to our definition would be a natural extension. Furthermore, building upon the long literature on peer effects, expanding the research to encompass other forms of social networks, such as neighbors, alumni, relatives, and social media connections, could provide a more comprehensive understanding of how these networks influence job choices and, consequently, the macroeconomy.

Our findings, inspired by the literature on outside options, raise questions about the potential impact of coworker networks on monopsony power in the labor market. This force is particularly relevant since our quantitative exercise shows that by promoting mobility, the existence of coworker networks may reduce average wages by increasing labor supply to growing sectors. This insight opens up opportunities to examine firm responses to changes in coworker networks and explore the interactions between firms and workers within this context. Additionally, future research can evaluate the impact of the coworker mechanism we uncover on other shocks or in different settings. For instance, an interesting application could involve embedding this mechanism into a trade model and examining its implications for labor market allocation following Germany's trade integration with Eastern European countries. Lastly, while our paper demonstrates a causal relationship between coworker composition and sector-switching decisions, it leaves room for further exploration of the specific mechanisms through which coworker networks operate. Unpacking these mechanisms is crucial for designing effective policies that enhance worker mobility and promote optimal labor allocation in support of industrial policies.

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Appendix

A Data Appendix

A.1 Data Construction

We use German Social Security records data spanning from 1975 to 2018 for our study. Specifically, we worked with the linked employer-employee data known as SIEED, which comprises a representative sample of 1.5% of establishments in Germany. This data set provides detailed employment biographies of individuals employed at the sampled establishments at the midpoint of each year. Two key features of this data set make it highly suitable for our research strategy, which focuses on examining the impact of information on industry choices. Firstly, the data set offers a comprehensive list of all employees within each establishment, allowing us to precise identify who the coworkers are for each job switcher. Secondly, the employment biographies are structured in a spell format, offering rich information about all jobs held by each individual. This allows us to identify job switchers as well as the previous sectors and occupations of employment for each of their coworkers.

Among all employees, we select only those that are liable to social security and without any special characteristics. We proceed as follows to construct the baseline sample for our individual-level analysis. First, we identify job switchers in a year by selecting all those who work in a different establishment compared to the one recorded in their previous spell. Second, we aggregate the data consisting of job spells into yearly cross sections by finding all workers who has ever been employed in a certain establishment at a given year. This allows us to identify all the coworkers for each job switcher. Note that our classification of coworkers only requires two individuals to be employed in the same establishment during the same year, but does not strictly require their employment dates to overlap.[44]

An important independent variable in our analysis is workers' wages. The SIEED dataset provides information on gross daily wage and daily benefits corresponding to each spell. To ensure comparability, we adjust all reported earnings to the 1975 Consumer Price Index (CPI). Notably, the dataset employs top-coding for earnings that surpass the upper limit set for statutory pension insurance. This ceiling varies over years and between eastern and western Germany. Employing the approach outlined by Dauth and Eppelsheimer (2020), we first ascertain whether each establishment is situated in eastern or western Germany using the provided federal state indicator. Subsequently, we determine the top-coding threshold for each establishment on an annual basis, aligned with its geographical location. As a final step, we convert all one-time payments to their corresponding daily values and combine them with the daily earnings. We generate a right-censored indicator by assuming that all daily wages amounting to at least 98% of the contribution assessment ceiling are censored. In the baseline analysis, we do not impute earnings above the upper threshold. Nevertheless, in one

[44] Even though we can identify employment biographies exactly to the day, we choose to define coworkers at the yearly level because the information left by an individual could still disseminate for some time after she leaves her current firm.

of our robustness tests, we check the relationship between coworker and elasticity of job choices to wage differential in an alternative sample where we exclude all workers with top-censored earnings.

Sample for Death and Retirement Analysis The steps we take to generate the sample used for our empirical analysis using coworker deaths and retirements are described as follow. First, we identify deaths from the "reason of cancellation/ notification/ termination" variable as employers are required to notify the Social Security system when an employment spell ends, including due to the reason of death. Similarly, we identify retirements from the same "reason of notification" variable with the caveat that it does not explicitly contain the category “deregistration due to retirement." Thus, we zoom into employees whose reasons for notification for their last job spell imply an end to their current employment. In particular, we require their “reasons for notification" variable to fall into one of the three categories: Deregistration due to end of employment, Deregistration due to interruption of employment for more than one month, and Simultaneous registration and deregistration due to end of employment. We then identify retired workers by choosing those whose age are close to the the legal age of retirement in Germany. After the initial step of identifying deceased and retired workers, we follow Jäger and Heining (2022) to rule out spurious deaths and retirements by including only those events with no subsequent reported spell that ends more than 30 days after. Furthermore, employees may start to work less in the months proceeding their deaths if they pass away due to chronic diseases. They may also enter partial retirement and reduce their working hours prior to officially retiring. Such cases would reduce the information content these workers bring about to their coworkers even in the periods leading up to worker death or retirement and obstruct our goal of using death and retirement as a sharp shock to incumbent workers' information sets. We therefore take two measures to ensure that the deaths events we focus on are sudden. First, we restrict to individuals who were employed full-time at the time of death or retirement. Second, we exclude those with more than 42 days of unemployment during their year of death or retirement. We next provide summary statistics on the establishment size distribution, the job switcher sample, the sector-level wage dynamics, and the job flows across sectors over time.

A.2 Wage Differential Imputation

Average wage by year, state, industry, and occupation As an initial step, we calculate $\hat{w}_{pjt}$ as the mean wage for workers in industry j, who have the same occupation as job switcher p before p switches job and whose place of work is located in the same federal state as the workplace for p. Because occupations are finely classified, it is plausible that workers are similar to those who are employed within the same occupation and would have received comparable job offers if they move to the same destination sector. Our model incorporates fixed effects for the interaction between occupation, industry, and time, as well as for the the interaction between location and time. Therefore, the predicted variation in wage differences we rely on primarily stems from distinctions across individuals and is driven by variations in their initial wages, w_{pit}.

AKM firm and worker fixed effects Secondly, as a refinement to the first approach, we additionally match the individual and her origin establishment to another worker-firm pair with similar characteristics in determining wages, using the person and firm fixed wage effects estimated from AKM. The detailed procedures are as follow. First, we find all individuals that switches from establishment e in year t. Second, for all the potential destination sectors, we find the average starting wage across all other individuals that switches into industry k during year t who are employed within the same occupation as individual p before they switch firms and whose person fixed effects estimated from AKM belong to the same vigintile as p. We in addition require that these individuals come from origin establishments the size of which belongs to the same quintile as e and the firm fixed effects of which belong to the same quantile as e.[45] The destination sector wages, $\hat{w}_{pjt}$, generated by this approach will not be entirely absorbed by the fixed effects and individual. Identification in this approach can thus also rely on the variation within individuals across the array of potential destination sectors, in addition to the variation across individuals in their starting wages.

Coworker wage Finally, we measure $\hat{w}_{jt}$ for an individual p by averaging the wage at the previous jobs across all p's current coworkers who last worked in industry j within the reference year t before transitioning to the current establishment. This approach assumes that workers who share similar job transition patterns are fundamentally comparable. As a result, we expect that workers who decide to transition to the same industry would likely have earned a comparable wage to their coworkers who recently left the previous industry of employment. Figure B3 shows the binscatter plot for imputed wages against the actual wages for the sector that each job switcher transitions into. It confirms that the imputed wage and the actual wage for job switchers are highly correlated, despite that the imputed wage compresses the wage distribution and overestimates wages at the bottom of the distribution. Figure B4 shows that there is still variation in all three wage measures after residualizing the imputed destination sector wage an individual could have earned on all other controls and fixed effects specified in the baseline regression.

A.3 Matching Method for Death and Retirement Analysis

We require exact matches for categorical characteristics, while we coarsen each one of the remaining continuous variables into quantiles. Using this method, we are able to find a match for 75% of the actual deaths or retirement events among those establishment-individual pairs that experience neither death or retirements. For a deceased or retired worker-firm pair in the treatment group that is matched to multiple worker-firm pairs without death, we calculate the propensity scores for these candidates who undergo the placebo death or retirement events and select the one with the closest propensity

[45] The individual and establishment fixed effects are ranked according to size and grouped into 20 quantiles by Bellmann et al. (2020).

score.[46] This matching process allows us to refine our dataset by retaining observations that lead to better balance between the treatment and control groups. Given the richness of the set of covariates in our dataset, achieving exact matches on the original variables would result in too few matches. We thus opt for exact matching on coarsened variables. The matching procedure enables us to not only control or the linear impact of individual- or firm-level characteristics but also accommodate arbitrary combinations of these characteristics at a coarser classification level. Thanks to the substantial size of our dataset, matching effectively mitigates bias without the disadvantages of reduced precision associated with smaller sample sizes. Additionally, with this reduced sample size, we can include all workers in both the treatment and control groups, as opposed to only job switchers in the baseline coworker analysis.[47]

In addition to matching each actual death or retirement event to a single placebo observation, we implement a sample restriction that confines our analysis to firms where the total workforce in either the treatment or control group falls within the range of 2 to 30 employees. We center our attention on small firms for two reasons. Firstly, the deaths and retirement of one worker in small firms is a sharper shock to workers' coworker compositions, as smaller firms tend to experience worker attrition due to death or retirement less frequently. Secondly, worker mortality and retirement better serve as a relevant proxy for the coworker composition in smaller firms, given that communication between each particular pairs of coworkers becomes less intense as the number of colleagues increases.[48] We thus do not lose much power by zooming into the smaller firms only. To mitigate the potential influence of work-related incidents impacting a substantial portion of employees, we exclude establishments encountering more than one worker fatality or retirement within a year.

[46]In the case where one placebo death or retirement has the higher propensity score among all observations that share all the coarsened attributes and is being matched to multiple observations in. Thus, we are using a matching with replacement strategy to ensure that the treatment and the control groups are similar, improving the quality of the matches.

[47]Since job switchers may make decisions differently from other workers, and our goal is to study the overall degree of sectoral allocation in the entire economy, we view the sample of all workers, as opposed to only the job switchers, as our preferred sample.

[48]On top of the two aforementioned reasons, our summary statistics reveal that the establishment size distribution is heavily right-skewed. Consequently, focusing solely on smaller firms doesn't substantially compromise our statistical power as there is still a sizable sample of workers being employed in these smaller establishments even though these establishments have fewer employees.

A.4 Summary Statistics for Baseline Analysis

Table A1: Establishment Size

Statistics	5%	10%	25%	50%	75%	90%	95%	Mean	Obs.
Value	1	1	3	11	52	261	727	200	101,563,311

Note: Table shows the distribution of establishment sizes in the data, pooled across all available years from 1975 to 2018. The number of observations statistics is at the establishment by year level. An establishment that appears in more than one year is being counted multiple times.

Table A2: Establishment-level Summary Statistics

Variable	Mean	Std.Dev.
Age	35.67	9.36
German	0.90	0.25
Female	0.45	0.44
Full-time	0.90	0.25
Tenure (years)	1.78	1.88
Real Wage	24.75	12.48
Wage Growth	0.01	0.37
Share Switching Job	0.56	0.37
Share Switching Sector	0.47	0.40

Note: Table shows the establishment-level summary statistics.

Table A3: Job Switchers vs. Job Stayers

	Switchers		Stayers	
	Mean	Std.Dev.	Mean	Std.Dev.
Age	33.89	10.22	35.58	10.56
German	0.90	0.30	0.90	0.30
Female	0.35	0.48	0.41	0.49
Full-time	0.92	0.27	0.91	0.29
Job tenure	2.11	3.03	2.41	3.49
Real Wage	29.08	14.69	30.47	15.47
Wage Growth	0.10	1.05	0.10	1.00
Count (000 000s)	6.7		10.2	

Note: Table shows the number of observations, the mean, and the standard deviation for characteristics separately for job switchers and job stayers, for years between 1975 and 2018. Variables "German", "Female", and "Full-time" are average shares. Job tenure is in years and wage growth is in decimal. An individual is defined as being a job switcher in that year if she switches establishment at any point in that given year. Statistics are calculated by pooling all job switchers and stayers across years.

Table A4: Coworker Shares by Sector

Sectors	Coworker Shares (Mean)	Coworker Shares (Std)
Agriculture and Mining	0.09	0.07
Manufacturing	0.11	0.20
Utilities, Water Supply, and Waste Management	0.01	0.05
Construction	0.08	0.04
Trade, Transportation, and Storage	0.16	0.25
Information and Professional Services	0.05	0.16
Financial, Insurance, and Real Estate	0.02	0.09
Accommodation, Administration, Arts, Other Services	0.19	0.26
Education and Health Services	0.07	0.18

Note: Table shows the average coworker share in an establishment last employed in a certain sector across all establishments used for the baseline analysis, for years between 1975 and 2018, and separately for each one of the nine sectors.

A.5 Summary Statistics for Death and Retirement Analysis

Table A5: Treatment vs. Control Groups at the Individual Level

	Treatment Group (Retirement)		Treatment Group (Death)		Control Group	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Age	41.96	11.42	39.84	10.87	40.87	11.29
German	0.93	0.45	0.93	0.26	0.93	0.26
Female	0.37	0.48	0.30	0.46	0.39	0.49
Full-time	0.95	0.23	0.94	0.23	0.94	0.24
Job tenure	4.90	5.83	5.28	5.88	4.49	5.10
Real Wage	34.87	17.20	37.46	16.17	34.00	16.46
Wage Growth	0.03	0.35	0.02	0.33	0.03	0.35
Person AKM Vigintile	9.94	5.49	10.52	5.26	9.84	5.44

Note: Table shows the mean and the standard deviation for characteristics separately for all the employees in establishments with retirement, all the employees in establishments with death, and all the employees in the establishments that belong to the control group, for years between 1975 and 2018. Variables "German", "Female", and "Full-time" are average shares. Job tenure is in years and wage growth is in decimal. All establishments in the control group are pooled together.

Table A6: Treatment vs. Control Groups at th Establishment Level

	Treatment Group (Retirement)		Treatment Group (Death)		Control Group	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Number of Workers	7.90	6.44	7.83	6.48	7.06	6.19
Number of New Hires	1.06	2.06	0.68	1.27	1.34	3.51
Number of Job Switchers	2.38	3.44	1.84	2.60	2.67	5.01
Firm AKM Vigintile	14.43	4.14	13.30	4.65	13.05	4.68

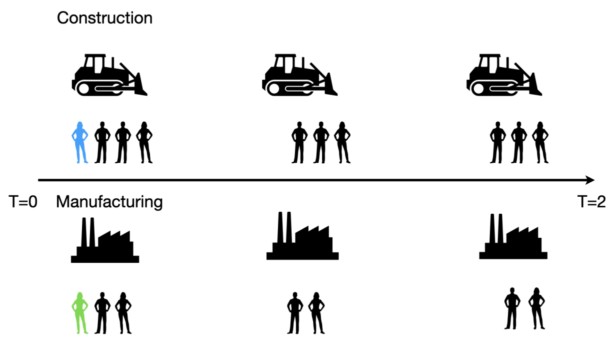
Note: Table shows the mean and the standard deviation for establishment-level characteristics separately for all establishments with retirement, all establishments with death, and all establishments belonging to the control group (pooled together across all establishments with either placebo death or placebo retirement).

B Empirical Approach

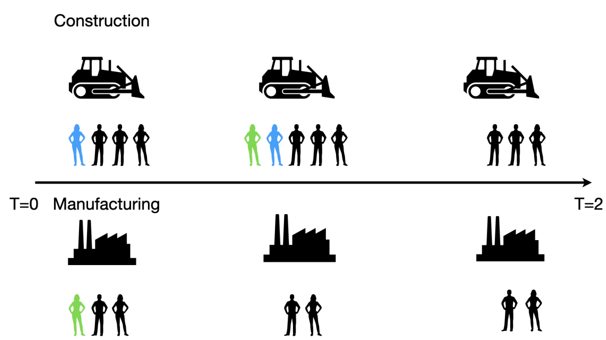
B.1 Graphical illustration

Figure B1: Definition of Coworker Networks

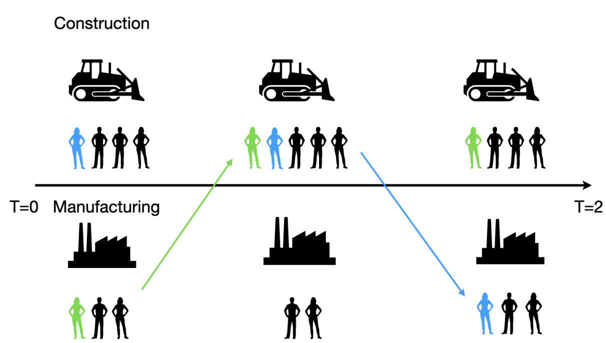
(A) T = 0



(B) T = 1



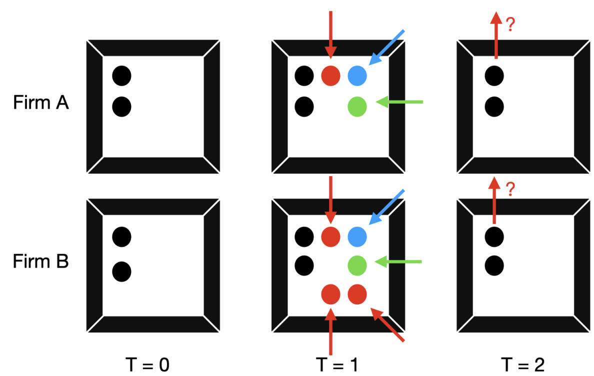
(C) T = 2



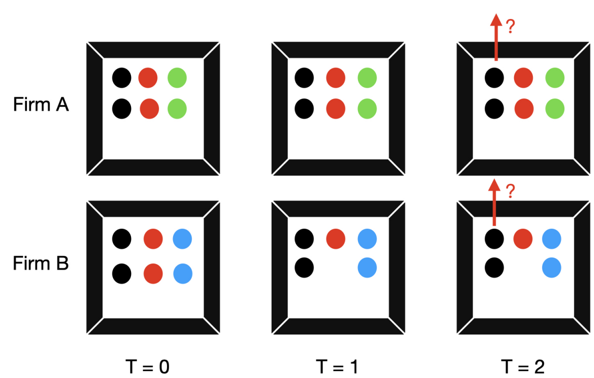
Note: Figure illustrates the relevant coworker network for our setting. We are interested in the colored individuals on each panel. At a certain point in time, the blue worker is employed in one sector (construction) and the green worker is employed in the another (manufacturing). At $T = 1$, the green individual moves to construction due to some idiosyncratic reasons and become a coworker of the blue individual at her current firm. We are interested in examining whether the blue individual is more likely to move to any firm in the green individual's previous sector, manufacturing.

Figure B2: Variation in Coworker Networks

(A) New Workers joining a Firm



(B) Incumbent Workers leaving a Firm

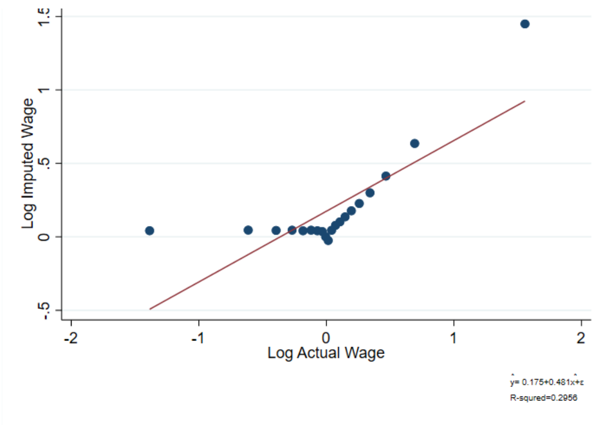


Note: Figure illustrates the identifying variation in coworker networks for our empirical strategy. Each square represents a firm and each dot an employee within the firm. The different previous sector of employment are represented by different colors. Panel (A) shows the identifying variation for our baseline regression. We compare two firms within the same sector. Some workers join both firms at T = 1 and leave the firms at T = 2. More workers from the red sector join firm B compared to firm A. We then compare, and we study whether incumbent workers in firm A are more likely to move to the red sector. Panel (B) shows the identifying variation for our death and retirement IV. Firm A and B start with similar worker composition in terms of previous sectors of employment. At T = 1, a worker previously employed in the red sector exit due to exogenous reasons (unexpected death or retirement) from firm B, but no worker exits in firm A. We study whether workers in firm B are less likely to move to the red sector.

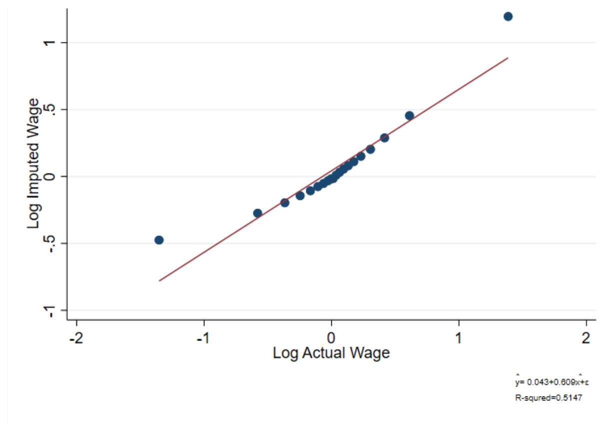
B.2 Imputed Wage

Figure B3: Imputed vs. Actual Wage

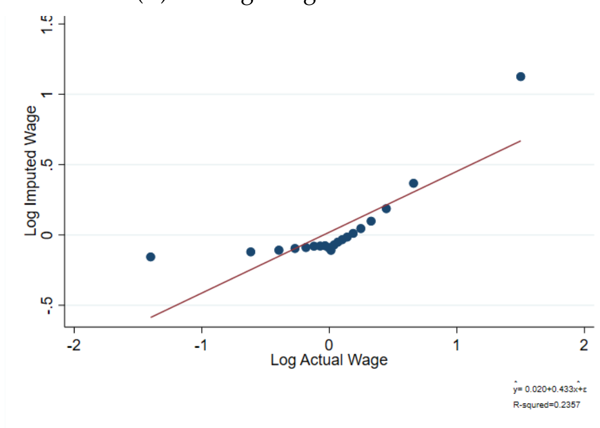
(A) Average by industry, occupation and state



(B) Average wage by AKM quantiles



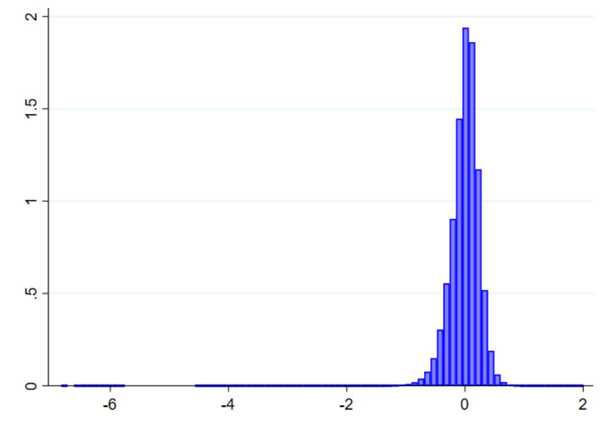
(C) Average wage of coworkers



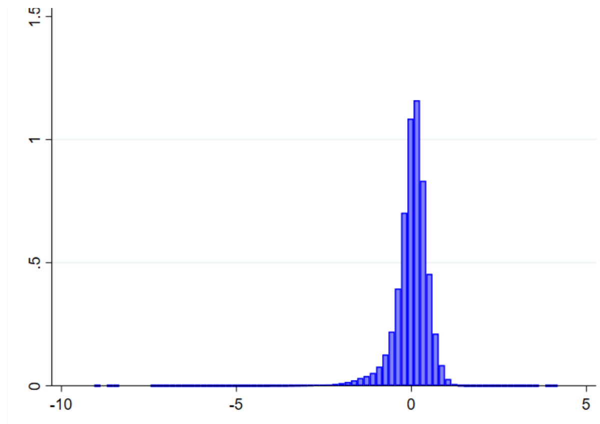
Note: Data source: SIEED. Figure plots binscatter of the difference between the logged imputed wage and the logged actual origin wage against the logged actual destination-sector wage and the logged actual origin wage for job switchers to confirm the validity of our approaches of measure wages in Section A.2. The red solid lines represent the fitted line. Panel (A) imputes wage by industry, occupation, state, and year. Panel (b) imputes wage by averaging wage across all those whose person- and firm-fixed effects estimated from an AKM regression both fall into the same quantiles. Panel (c) imputes wage by averaging across all coworkers at the workers' current firm who just transitioned from the industry that the coworker will move into.

Figure B4: Variation in Residualized Imputed Wage

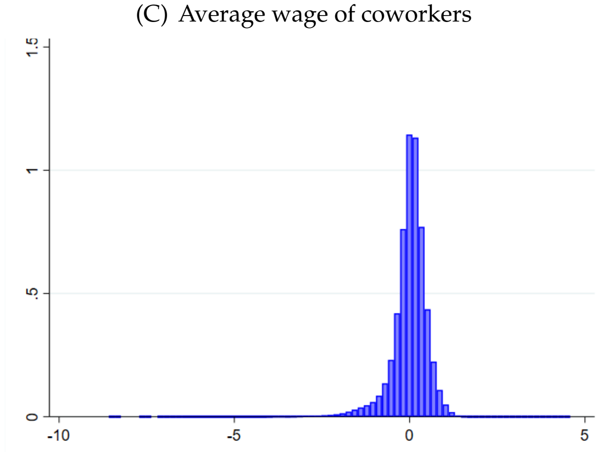
(A) Wage approximated by industry, occupation, and state



(B) Wage approximated by AKM quantiles



(C) Average wage of coworkers



Note: Data source: SIEED. Figure plots the histogram of the residualized wage measures by regression imputed destination-sector wage on all other controls and fixed effects specified in (1). Panel (A) imputes wage by industry, occupation, state, and year. Panel (b) imputes wage by averaging wage across all those whose person- and firm-fixed effects estimated from an AKM regression both fall into the same quantiles. Panel (c) imputes wage by averaging across all coworkers at the workers' current firm who just transitioned from the industry that the coworker will move into.

B.3 Additional Empirical Results

B.3.1 Worker Heterogeneity

The first dimensions of heterogeneity that we examine are across gender and nationality. We re-run specification 1 separately for men vs. women, and Germans vs. Non-Germans. The destination-sector wage $\hat{w}_{pjt}$ is being constructed in the same way as in the baseline, but independently for each gender, and for Germans vs. foreigners. Panel (A) of Table B1 shows that the relationship between the share of current coworkers last employed in a certain industry and the individual propensity to move to that sector exists across workers with different genders and nationalities. The magnitude of the coefficient estimates of interest, $\hat{\alpha}_2$ and $\hat{\beta}_1$ are comparable to those in the baseline. We find that the influence of previous coworkers on the responsiveness to differences in wages are close to identical for both genders, and for both domestic and foreign workers. Having more coworkers who transitioned from a certain industry is associated with slightly higher likelihood of moving to that sector on average for male and German workers.

In addition to gender and nationality, we further explore the heterogeneous effects by analyzing workers in distinct age and tenure quintiles. Panel (B) and (C) of Table B1 demonstrate that the impact of coworkers on sectoral choice elasticity, with respect to wage differentials, is significant across all age and tenure quintiles. However, the effect is notably less pronounced–with the magnitude of the coefficient estimates for $\hat{\alpha}_2$ being around half compared to the other groups–for the youngest workers as well as those with the shortest tenure, while remaining relatively consistent across other age and tenure groups. This is consistent with the explanations that young workers and workers with shorter tenures may be less aware of or responsive to better outside options, as represented by their higher wages, due to limitations in their work experiences and financial resources, or concerns of job security and attempts to prioritize learning and growth opportunities over current wages.

Table B1: Impact of Coworkers on Sector-Switching, by Worker Characteristics

	(1)	(2)	(3)	(4)	(5)
	Panel (A): Gender and Nationality				
	Male	Female	German	Non-German	
Coworker	0.123***	0.109***	0.114***	0.121***	
	(0.0010)	(0.0013)	(0.0017)	(0.0009)	
ln(Wage Diff)	0.004***	0.006***	0.002***	0.006***	
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Coworker × ln(Wage Diff)	0.036***	0.036***	0.034***	0.033***	
	(0.0012)	(0.0014)	(0.0023)	(0.0010)	
Mean of Dep. Var	0.073	0.074	0.073	0.074	
R^2	0.32	0.31	0.40	0.31	
Observations	94,210,240	56,977,554	14,776,011	136,408,129	
	Panel (B): Age Quintiles				
Coworker	0.079***	0.118***	0.133***	0.149***	0.171***
	(0.0008)	(0.0011)	(0.003)	(0.0016)	(0.0022)
ln(Wage Diff)	0.004***	0.005***	0.005***	0.005***	0.005***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Coworker × ln(Wage Diff)	0.018***	0.036***	0.039***	0.034***	0.042***
	(0.0014)	(0.0017)	(0.0016)	(0.0020)	(0.0024)
Mean of Dep. Var	0.083	0.075	0.070	0.067	0.062
R^2	0.37	0.31	0.29	0.28	0.26
Observations	47,061,425	29,742,688	33,281,554	22,102,115	18,843,929
	Panel (C): Tenure Quintiles				
Coworker	0.079***	0.121***	0.138***	0.154***	0.177***
	(0.0008)	(0.0011)	(0.0012)	(0.0015)	(0.0021)
ln(Wage Diff)	0.003***	0.005***	0.005***	0.005***	0.005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Coworker × ln(Wage Diff)	0.014***	0.032***	0.033***	0.029***	0.032***
	(0.0013)	(0.0017)	(0.0016)	(0.0019)	(0.0024)
Mean of Dep. Var	0.083	0.075	0.070	0.067	0.062
R^2	0.37	0.31	0.29	0.28	0.26
Observations	47,055,187	29,745,723	33,271,123	22,094,320	18,838,162

Notes: Table displays $\hat{\alpha}_1, \hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for specification (1). Standard errors are clustered at the origin establishment level. The dependent variable in all regressions is the probability of switching to a certain destination sector. In Panel (A), first and second columns use the samples of males and females only. Third and Fourth columns use the samples of non-Germans and Germans only. Panel (B) displays the estimates obtained separately for different quintiles of the age distribution, with column (1) being the youngest age quintile and column (5) being the oldest age quintile. Panel (C) displays the estimates obtained separately for different quintiles of the tenure distribution, with column (1) being the group with the shortest tenure and column (5) being the group with the longest tenure.

B.3.2 Robustness

Table B2: Estimation Results for Specification (1) with different wage measure

	(1)	(2)
Coworker	0.096***	0.172***
	(0.0011)	(0.0015)
ln(Wage Diff)	0.003***	0.005***
	(0.0002)	(0.0003)
Coworker × ln(Wage Diff)	0.032***	0.057***
	(0.0009)	(0.0014)
Coworker Wage	✓	
AKM Wage		✓
Mean of Dep. Var	0.150	0.305
R^2	0.34	0.36
Observations	37,798,210	26,627,735

Notes: Table displays $\hat{\alpha}_1, \hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for specification (1). Standard errors are clustered at the origin establishment level. The dependent variable in all regressions is the probability of switching to a certain destination sector. Column (1) approximates workers' wages using their coworkers at the current establishment who was established in the reference destination industry before. Column (2) approximates workers' wages using the average of those with the same AKM firm and individual fixed effects within the industry in a given reference year.

Table B3: Estimation Results for Specification (1) with different coworker controls

	(1)	(2)
Coworker	0.117***	0.147***
	(0.0009)	(0.0011)
ln(Wage Diff)	0.003***	0.003***
	(0.0001)	(0.0001)
Coworker × ln(Wage Diff)	0.038***	0.021***
	(0.0009)	(0.0006)
Separate controls	✓	
One-year lag		✓
Mean of Dep. Var	0.06	0.06
R^2	0.32	0.32
Observations	196,592,086	159,469,014

Notes: Table displays $\hat{\alpha}_1, \hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for specification (1). Standard errors are clustered at the origin establishment level. The dependent variable in all regressions is the probability of switching to a certain destination sector. Column (1) approximates controls for additionally the interaction between the non-current-year coworker share and the wage differential. Column (2) controls for one-year lagged coworker share instead of non-current-year coworker share.

B.3.3 Alternative Samples

We assess in alternative samples the robustness of the correlation between the past sectoral composition of individuals' coworkers and their responsiveness to potential wage differentials, as highlighted in our baseline analysis. Our first modification introduces an additional sample restriction by excluding workers who change geographies alongside job switches. Migration decisions may be influenced by external factors, and individuals who relocate for work are subject to idiosyncratic reasons, thus potentially responding less to wage increases and diverging in behavior from those who remain in the same location. We also omit from the sample all workers whose wages are top-coded in the data.

Our next modification addresses a potential issue with the key independent variable in our baseline regression, which is the current-year coworker share within an establishment that just transitioned from each of the other sectors. Since each firm tends to experience worker inflows from a certain subset of all sectors, this design implies that a substantial amount of the key independent variable is zero-valued. These zeros may be structural, representing fundamental differences between the origin firm and the destination sector of interest and resulting in job transition behaviors that are different from other firm-sector pairs with non-zero flows. This may introduce bias to the regression estimate. To mitigate this concern, we re-run the baseline regression in an alternative sample where we exclude all origin establishment and destination sector combinations in which the establishment previously experienced no inflow from that sector of interest.

Lastly, to alleviate the concern that decisions of workers who move back to their previous sectors may be driven more by their personal experiences and skills than the information or skills brought by their current coworkers, we exclude such workers from our analysis. Nevertheless, despite the fact that workers who transition back into their past sector may act differently than others who transition into a sector where they have little previous experience, it is plausible and likely that coworkers still play a role in affecting the decisions made by such workers. This specification may therefore be interpreted as a lower bound for measuring the importance of coworker networks in individuals' sectoral choice decisions.

The results are presented in the first four columns of Table B5. The coefficient estimates for $\hat{\alpha}_1$ in the specifications excluding geography-switching, top-coded wages, or zero-valued flows are all roughly comparable to our baseline estimates. In the specification where we exclude job switchers who return to work in their past sector, the magnitude of $\hat{\alpha}_1$ is approximately 60% of the baseline estimate. This result is expected since workers tend to transition more to sectors where they previously worked, while having more coworkers from that sector. Such correlation may be due to idiosyncratic reasons not captured by the fixed effects or the non-overlapping coworker shares. Excluding these observations lowers the coefficient estimate. However, the effect of coworkers on the average propensity to transfer to a destination sector remains positive and significant even in this specification.

Regarding the switching elasticity with respect to potential wage differentials, in columns (1) and (2), the estimates of $\hat{\alpha}_2$ are larger than the baseline. This indicates that the effect of having more coworkers previously employed in a sector on the increased responsiveness to wage gains in those sectors is even stronger for workers who do not switch states and who are not at the very top of the income distribution. These results may be justified by the fact that migrants—who switch jobs due to personal reasons unrelated to employment—and top earners—who derive less marginal utility from an increase in disposable income—are not as sensitive to wage changes as other workers. The $\hat{\alpha}_2$ estimates for the sample excluding establishment-sector pairs with zero coworker flows and for the sample excluding individuals switching back to their previous sectors are only slightly smaller than the baseline. This provides evidence that the effect persists after excluding cases in which workers may make decisions differently and based on factors not necessarily accounted for by our control variables.

B.3.4 Establishment-Level Evidence

To examine whether the relationship between information and job transition across industries still holds when classifying industries into finer categories, we supplement our individual-level regression with establishment-level analysis.[49] Our baseline specification for the establishment-analysis is implemented for any establishment e, and follows:

$$\begin{aligned}\pi_{eijt} =&\alpha_0 + \alpha_1(\ln w_{jt} - \ln w_{et}) + \alpha_2\tilde{\theta}_{ejt} \times (\ln w_{jt} - \ln w_{et}) + \\ &\beta_1\tilde{\theta}_{ejt} + \beta_2\frac{1}{T-1}\sum_{k\neq t}\theta_{ejk} + \zeta_{ijt} + \xi_{l(e,t)t} + \Gamma X_{eijt} + \varepsilon_{ejt}\end{aligned} \tag{40}$$

π_{eijt} is the share of workers who move to destination industry j among all job switchers that leave establishment e in t, which belongs to origin industry i. We stack all destination industries and set $\pi_{eijt} = 0$ if establishment e has no worker outflow to industry j. w_{jt} is the average wage for industry j at time t, and w_{et} is the average wage across all occupations for establishment e at time t. Similar to the individual regression, $\tilde{\theta}_{ejt} = \theta_{pjt} - \frac{1}{T-1}\sum_{k\neq t}\theta_{ejk}$ is the difference between the current-year worker share and non-current-year worker share employed in establishment e that came from industry j. ζ_{ijt} is the set of origin-by-destination-by year fixed effects that control for time-varying shocks hitting the origin and destination sectors alone, or the ones that affect the difficulty in transition between pairs of industries. $\xi_{l(e,t)t}$ is the set of location-by-year fixed effects. Control variables X_{eijt} include establishment size, the fraction of employees that are German, female, full-time, skilled in establishment e, switched location when switching jobs, as well as the average level of vocational training, age, job tenure, and days of unemployment in the current calendar year of in the establishment. This is the set of controls included in all establishment-level regressions, unless otherwise stated. The analysis

[49]Because regression specification (1) pool across all possible destination sectors and each individual observation appears multiple times, using a finer would pose a significant computation challenge. Finer industry classification is feasible in the establishment-level analysis when the number of job switchers greatly exceeds the number of establishments.

is at the division level and there are 19 divisions in total.[50] Standard errors are classified at the origin establishment level.

Column (5) of Table B5 presents the outcomes obtained by estimating the regression specification outlined in Equation (40). Notably, the wage measure at the establishment level, which amalgamates various occupations, introduces more noise in comparison to the wage measure utilized in our individual-level analysis. Consequently, this increase in noise results in a notably smaller estimate for the main effect of sectoral move propensity concerning the imputed wage differential, denoted as $\hat{\alpha}_1$. However, the estimate for $\hat{\alpha}_2$ is still statistically significant and of larger magnitude. This outcome aligns with expectations, as switching industry in a more granular sense may be both easier and more commonplace than switching sector. Such job transition patterns may be attributed to the fact that many skills, knowledge, and connections are often specific to particular sectors.

Table B4: Estimation Results for Specification (1) with different controls

	(1)	(2)	(3)	(4)	(5)
Coworker	0.297***	0.295***	0.255***	0.244***	0.251***
	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0014)
ln(Wage Diff)	0.007***	0.005***	0.012***	0.013***	0.011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Coworker × ln(Wage Diff)	0.045***	0.046***	0.042***	0.044***	0.044***
	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0014)
Worker Characteristics		✓	✓	✓	✓
Origin FE			✓	✓	✓
Destination FE			✓	✓	✓
Year FE			✓	✓	✓
State FE			✓	✓	✓
Origin × Destination × Year FE				✓	
Occupation FE					✓
Mean of Dep. Var	0.073	0.073	0.073	0.073	0.074
R^2	0.05	0.05	0.07	0.08	0.07
Observations	161,778,363	152,859,232	152,855,734	152,855,734	151,247,674

Notes: Table displays $\hat{\alpha}_1$, $\hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for specification (1). Standard errors are clustered at the origin establishment level. The dependent variable in all regressions is the probability of switching to a certain destination sector. Column (1) does not include any control variable (no $X_{pijt}, \zeta_{io(p,t)jt}, \xi_{l(p,t)t}$). Column (2) controls for all worker characteristics specified in section 2.1. Column (3) includes the origin sector fixed effects, destination sector fixed effects, year fixed effects, state fixed effects separately. Column (4) includes the origin-by-destination-by yer fixed effects in interactions. Column (5) additionally controls for the occupations fixed effects.

[50]Specifically, we follow the Nomenclature of Economic Activities (NACE) code, which is the European statistical classification of economic activities. There are 20 divisions according to this classification, and we aggregate the three smallest divisions–"Other Service Activities", "Activities of Households as Employers; Undifferentiated Goods- and Services-producing Activities of Households for Own Use", and "Activities of Extraterritorial Organizations and Bodies"–into one single category, resulting in 19 divisions in total for the analysis.

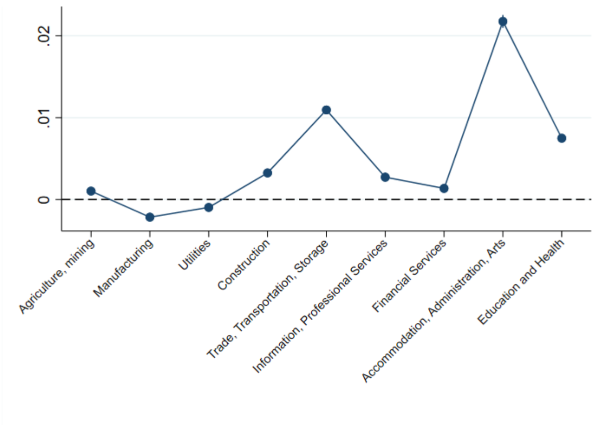
Table B5: Estimation Results for Specification (1) with alternative samples

	(1)	(2)	(3)	(4)	(5)
Coworker	0.114***	0.113***	0.149***	0.071***	0.091***
	(0.0010)	(0.0008)	(0.0011)	(0.0019)	(0.0002)
ln(Wage Diff)	0.006***	0.005***	0.006***	0.003***	0.0001***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0000)
Coworker × ln(Wage Diff)	0.039***	0.040***	0.022***	0.030***	0.044***
	(0.0011)	(0.0009)	(0.0009)	(0.0019)	(0.0002)
Exclude Geography Switching	✓				
Exclude Top-coded Wages		✓			
Exclude Zero-valued Flows			✓		
Exclude Switching to Past Sector				✓	
Establishment-level Analysis					✓
Mean of Dep. Var	0.072	0.074	0.130	0.057	0.131
R^2	0.32	0.32	0.32	0.28	0.15
Observations	124,941,253	145,494,761	39,571,954	149,917,307	47,966,424

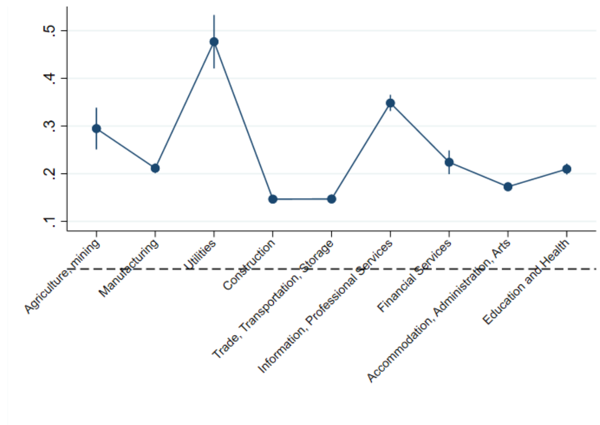
Notes: Column (1) - (4) of table display $\hat{\alpha}_1, \hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for specification (1). The dependent variable in the regressions for columns (1) - (3) in is the probability of switching to a certain destination sector. First column excludes job switchers who also switch states. Second column excludes workers with top-coded wages. Third column excludes establishment-sector shares with size-zero flows. Fourth column excludes workers who switch back to their past sector of employment. Column (5) of table displays $\hat{\alpha}_1, \hat{\beta}_1$, and $\hat{\alpha}_2$ estimated for regression specification (40).

Figure B5: Estimation Results for Specification 1 by Destination Sector

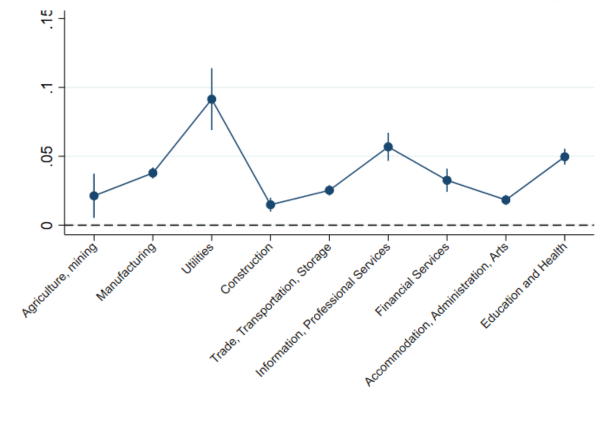
(A) Coefficient estimates on wage, $\frac{\ln \hat{w}_{pjt}}{\ln w_{pit}}$



(B) Coefficient estimates on coworker share, $\tilde{\theta}_{pjt}$



(C) Coefficient estimates on interaction, $\tilde{\theta}_{pjt} \times \frac{\ln \hat{w}_{pjt}}{\ln w_{pit}}$



Note: Data source: SIEED. Figure plots the histogram of the residualized wage measures by regression imputed destination-sector wage on all other controls and fixed effects specified in (1). Figure plots Panel (A) imputes wage by industry, occupation, state, and year. Panel (b) imputes wage by averaging wage across all those whose person- and firm-fixed effects estimated from an AKM regression both fall into the same quantiles. Panel (c) imputes wage by averaging across all coworkers at the workers' current firm who just transitioned from the industry that the coworker will move into.

Table B6: Estimation results for death and retirement IV

	(1)	(2)	(3)
Coworker	0.023***	0.032**	0.084***
	(0.0037)	(0.0144)	(0.0122)
ln(Wage Diff)	0.017***	0.020***	0.008**
	(0.0011)	(0.0041)	(0.0038)
Coworker × ln(Wage Diff)	0.031***	0.041**	0.060***
	(0.0046)	(0.0196)	(0.0174)
Sample	All	Est. with Deaths	New Hires
Mean of Dep. Var	0.061	0.066	0.137
Observations	4,999,720	338,141	572,361

Notes: Table displays $\hat{\alpha}_1$ and $\hat{\alpha}_2$ estimated for specification (7). Standard errors are clustered at the origin establishment level. In all regressions, we control for the origin-by-industry-by-occupation-by year fixed effects. Destination industry at the 3-digit NACE code level. The dependent variable for columns (1) - (2) is the firm fixed effect quantiles estimated from an AKM regression at the new job. Firms are categorized into 20 quantiles in total. The dependent variables for columns (3) - (4) is the tenure at the new job. Columns (2) and (4) control for the person fixed effect quantiles estimated from an AKM regression for each job switcher and the logged wage at the new job.

C Background Information

Figure C1: Timeline of Events of COVID-19 in Germany

Note: Figure illustrates the timing of the major events related to COVID-19 in Germany.

D Model Derivations

D.1 Proof of Proposition 1

According to Small and Rosen (1981), $\nu \log \sum_{dh} \exp(V^{dh}/\nu) + \nu C = \mathbb{E}_e[\max_{dh}(V^{dh} + \nu e^{dh})]$, where e^{dh} is from a Type-I extreme value distribution and C is Euler's constant. Applying this result, we can rewrite the HJB equation as:

$$\begin{aligned}
&\rho v_t^{jn} - \mathbb{E}[\frac{\partial v_t^{jn}}{\partial t}] \\
&= u(c_t^{jn}) + \phi \left\{ \max_{d,h} \mathbb{E}[v_t^{dh}] - \kappa_t^{jn,dh} + \nu(\epsilon_{0,t}^{h} + \zeta \epsilon_{1,t}^{dh}) - V_t^{jn} \right\} \\
&= u(c_t^{jn}) + \phi \left\{ \max_{h \in \mathcal{N}} \nu\zeta \log \left(\sum_{d \in \mathcal{M}_h} \exp\left[\frac{1}{\nu\zeta} \left(\mathbb{E}[v_t^{dh}] - \kappa_t^{jn,dh} \right) \right] \right) + \nu \epsilon_{0,t}^{h} - V_t^{jn} \right\} \\
&= u(c_t^{jn}) + \phi \left\{ \max_{h \in \mathcal{N}} \nu\zeta \log \left(\sum_{d \in \mathcal{M}_h} \exp\left[\frac{1}{\nu\zeta} \left(\mathbb{E}[v_t^{dh}] - \kappa_t^{jn,dh} \right) \right] \right) + \nu \epsilon_{0,t}^{h} - V_t^{jn} \right\}
\end{aligned}$$

Within a sector k, the probability of moving to a firm k is given by:

$$\begin{aligned}
&\mu_t^{jn,ik|k} = P\Big[\mathbb{E}\left[v_t^{ik}\right] - \kappa_t^{jn,ik} + \nu\zeta\epsilon_{1,t}^{ik} > \max_{r \neq i, r \in \mathcal{M}_k} \mathbb{E}\left[v_t^{rk}\right] - \kappa_t^{jn,rk} + \nu\zeta\epsilon_{1,t}^{rk}\Big] \\
&= P\left[\frac{1}{\rho+\phi}\mathbb{E}\left[u(c_t^{ik}) - \frac{dv_t^{ik}}{dt} + \hat{V}_t^{ik}\right] - \kappa_t^{jn,ik} + \nu\zeta\epsilon_{1,t}^{ik} > \max_{r \neq i, r \in \mathcal{M}_k} \frac{1}{\rho+\phi}\mathbb{E}\left[u(c_t^{rk}) - \frac{dv_t^{rk}}{dt} + \hat{V}_t^{rk}\right] - \kappa_t^{jn,rk} + \nu\zeta\epsilon_{1,t}^{rk}\right] \\
&= P\Bigg[\frac{1}{\rho+\phi}\Big[\beta_1 l_t^{k,jn}\log(B^{ik}) + \log(Z_t^k) - \gamma\log(L_t^{ik}) + \log(p_t^n(1-\gamma)/P_t) - \\
&\quad \mathbb{E}[\frac{\partial V_t^{ik}}{\partial t}] + \hat{V}_t^{ik}\Big] - \kappa_t^{jn,ik} + \nu\zeta\epsilon_{1,t}^{ik} > \max_{r \neq i, r \in \mathcal{M}_k} \frac{1}{\rho+\phi}\Big[\beta_1 l_t^{rk,jn}\log(B^k) + \\
&\quad \log(Z_t^k) - \gamma\log(L_t^{rk}) + \log(p_t^n(1-\gamma)/P_t) - \mathbb{E}[\frac{\partial V_t^{rk}}{\partial t}] + \hat{V}_t^{rk}\Big] - \kappa_t^{jn,rk} + \nu\zeta\epsilon_{1,t}^{rk}\Bigg] \\
&= P\left[V_t^{ik} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{ik}) - \kappa_t^{jn,ik} + \nu\zeta\epsilon_{1,t}^{ik} > \max_{r \neq i, r \in \mathcal{M}_k} V_t^{tk} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - \kappa_t^{jn,rk} + \nu\zeta\epsilon_{1,t}^{rk}\right]
\end{aligned}$$

where we denote by $\hat{V}_t^{ik}$ the continuation value of being in firm ik plus the current value function $\mathcal{V}_t^{ik}$ in the intermediate steps. Note that $\max_{r \neq i, r \in \mathcal{M}_k} V_t^{rk} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - \kappa_t^{jn,rk} + \nu\zeta e_t^{rk}$ is distributed according to a Gumbel distribution:

$$\begin{aligned}
&\max_{r \neq i, r \in \mathcal{M}_k} V_t^{rk} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - \kappa_t^{jn,rk} + \nu\zeta\epsilon_{1,t}^{rk} \sim \\
&Gumbel\left(\nu\zeta \log \sum_{r \neq i, r \in \mathcal{M}_k} \exp\left[\frac{1}{\nu\zeta}\left(V_t^{rk} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - \kappa_t^{jn,rk}\right)\right], \nu\zeta\right)
\end{aligned}$$

The term at the left side of the inequality is also distributed according to a Gumbel distribution:

$$V_t^{ik} + \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\left(\bar{b}^k - \log(B^{ik})\right) - \kappa_t^{jn,ik} + \nu\zeta\epsilon_{1,t}^{rk} \sim Gumbel(V_t^{ik} + \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\left(\bar{b}^k - \log(B^{ik})\right) - \kappa_t^{jn,ik}, \nu\zeta)$$

Since the probability that a random variable X distributed according to $Gumebl(\mu_X, \sigma)$ is greater than another random variable Y distributed according to $Gumbel(\mu_Y, \sigma)$ is given by:

$$P(X > Y) = \frac{\exp(\mu_X)^{\frac{1}{\sigma}}}{\exp(\mu_X)^{\frac{1}{\sigma}} + \exp(\mu_Y)^{\frac{1}{\sigma}}}$$

We can obtain that the firm-level choice probability is equal to:

$$\begin{aligned}
\mu_t^{jn,ik|k} =& \frac{\exp\left(V_t^{ik} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_t^{ik,jn})\bar{\kappa}^{jn,ik}\right)^{\frac{1}{\nu\zeta}}}{\exp\left(\frac{V_t^{ik} - \frac{1-\beta_1 l_t^{ik,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_t^{ik,jn})\bar{\kappa}^{jn,ik}}{\nu\zeta}\right) + \sum_{r\neq i, r\in\mathcal{M}_k}\exp\left[\frac{V_t^{rk} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_t^{rk.jn})\bar{\kappa}^{jn,k}}{\nu\zeta}\right]} \\
=& \frac{\exp\left(V_t^{ik} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_t^{ik,jn})\bar{\kappa}^{jn,ik}\right)^{\frac{1}{\nu\zeta}}}{\sum_{r\in\mathcal{M}_k}\exp\left(V_t^{rk} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_t^{rk,jn})\bar{\kappa}^{jn,rk}\right)^{\frac{1}{\nu\zeta}}}
\end{aligned}$$

To derive the expression for sector-level choice probabilities, we write the expected value of switching to any firm within a sector k for an individual employed in firm jn as:

$$\begin{aligned}
&\tilde{S}_t^{jn,k} = \log\left[\sum_{r\in\mathcal{M}_k}\exp\left(\frac{1}{\nu\zeta}(\mathbb{E}[V]_t^{rk} - \kappa_t^{jn,rk})\right)\right] \\
=&\log\left[\sum_{r\in\mathcal{M}_k}\exp\left(\frac{1}{\nu\zeta}\left(V_t^{rk} + \frac{1-\beta_0 l_t^{k,jn}}{\rho+\phi}(\bar{z} - \log(Z_t^k)) - \frac{1-\beta_1 l_t^{ik,jn}}{\rho+\phi}\log(B^{rk}) - \left((1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k} + (1-\alpha_1 l_t^{ik,jn})\right)\right)\right] \\
=&\log\left[\sum_{r\in\mathcal{M}_k}\exp\left(\frac{1}{\nu\zeta}\left(V_t^{rk} - \frac{1-\beta_1 l_t^{ik,jn}}{\rho+\phi}\log(B^{rk}) - \left(1-\alpha_1 l_t^{ik,jn}\right)\bar{\kappa}^{jn,ik}\right)\right]+ \\
&\frac{1}{\nu\zeta}\frac{1-\beta_0 l_t^{k,jn}}{\rho+\phi}(\bar{z} - \log(Z_t^k)) - \frac{1}{\nu\zeta}(1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k} \\
=&S_t^{jn,k} + \frac{1}{\nu\zeta}\frac{1-\beta_0 l_t^{k,jn}}{\rho+\phi}(\bar{z} - \log(Z_t^k)) - \frac{1}{\nu\zeta}(1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k}
\end{aligned}$$

where we denote $S_t^{jn,k} = \log\left[\sum_{r\in\mathcal{M}_k}\exp\left(\frac{1}{\nu\zeta}\left(V_t^{rk} - \frac{1-\beta_1 l_t^{ik,jn}}{\rho+\phi}\log(B^{rk}) - \left(1-\alpha_1 l_t^{ik,jn}\right)\bar{\kappa}^{jn,ik}\right)\right]$.

The probability of moving into a sector k is given by:

$$\mu_t^{jn,k} = P\left[\nu\zeta\tilde{S}_t^{jn,k} + \nu\epsilon_{0,t}^k > \max_{h\neq k, h\in\mathcal{N}}\nu\zeta\tilde{S}_t^{jn,h} + \nu\epsilon_{0,t}^h\right]$$

Note that $\max_{h\neq k, h\in\mathcal{N}}\nu\zeta\tilde{S}_t^{jn,h} + \nu\epsilon_{0,t}^h$ and $\nu\zeta\tilde{S}_t^{jn,k} + \nu\epsilon_{0,t}^k$ are both also distributed according to Gumbel distributions:

$$\max_{h\neq k,h\in\mathcal{N}} \nu\zeta\tilde{S}_t^{jn,h} + \nu\epsilon_{0,t}^h \sim Gumbel\Big(\nu\log\sum_{h\neq k,h\in\mathcal{N}}\exp(\zeta\tilde{S}_t^{jn,h}),\nu\Big)$$

$$\nu\zeta\tilde{S}_t^{jn,k} + \nu\epsilon_{0,t}^k \sim Gumbel(\nu\zeta\tilde{S}_t^{jn,k},\nu)$$

We can then obtain that the sector-level choice probability is equal to:

$$\begin{aligned}\mu_t^{jn,k} &= \frac{\exp(\zeta\tilde{S}_t^{jn,k})}{\exp(\zeta\tilde{S}_t^{jn,k}) + \sum_{h\neq k,h\in\mathcal{N}}\exp(\zeta\tilde{S}_t^{jn,h})} = \frac{\exp(\zeta\tilde{S}_t^{jn,k})}{\sum_{h\in\mathcal{N}}\exp(\zeta\tilde{S}_t^{jn,h})} \\ &= \frac{\exp\left(\zeta S_t^{jn,k} + \frac{1-\beta_0 l_t^{k,jn}}{\nu(\rho+\phi)}(\bar{z}-\log(Z_t^k)) - \frac{1-\alpha_0 l_t^{k,jn}}{\nu}\bar{\kappa}^{n,k}\right)}{\sum_{h\in\mathcal{N}}\exp\left(\zeta S_t^{jn,h} - \frac{1-\beta_0 l_t^{h,jn}}{\nu(\rho+\phi)}(\bar{z}-\log(Z_t^h)) - \frac{1-\alpha_0 l_t^{h,jn}}{\nu}\kappa^{n,h}\right)}\end{aligned}$$

And the HJB equation can be written as:

$$\begin{aligned}&\rho V_t^{jn} - \mathbb{E}[\frac{dV_t^{jn}}{dt}] \\ =&u(c_t^{jn}) + \phi\Bigg\{\nu\log\sum_{h\in\mathcal{N}}\exp\left(\zeta\log\sum_{d\in\mathcal{M}_h}\exp\left[\frac{1}{\nu\zeta}\Big(V_t^{dh} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B)^{ik} - (1-\alpha_1 l_t^{ik,jn})\bar{\kappa}^{jn,ik}\Big)\right]+\right. \\ &\left.\frac{1-\beta_0 l_t^{k,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z_t^k)\Big) - (1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k}\right) - V_t^{jn}\Bigg\}\end{aligned}$$

D.2 Poof of Proposition 2

D.2.1 Flow payoffs

We solve for equilibrium prices and wages as a function of the distribution of workers at each firm. Firm's first-order condition implies that:

$$w_t^{jn} = p_t^n(1-\gamma)B^{jn}Z_t^n(L_t^{jn})^{-\gamma},\ Z_t^n = \tilde{Z}^n\exp(\epsilon\delta^n z_t)$$

Household demand for the firm-specific goods clears the goods market:

$$\chi^n\sum_{k\in\mathcal{N}}p_t^kZ_t^k\sum_{i\in\mathcal{M}_k}B^{ik}(L_t^{ik})^{1-\gamma} = p_t^nZ_t^n\sum_{j\in\mathcal{M}_n}B^{jn}(L_t^{jn})^{1-\gamma}$$

Now, let's write:

$$p_t^n = \frac{\chi^n\sum_{k\in\mathcal{N}}p_t^kZ_t^k\sum_{i\in\mathcal{M}_k}B^{ik}(L_t^{ik})^{1-\gamma}}{Z_t^n\sum_{j\in\mathcal{M}_n}B^{jn}(L_t^{jn})^{1-\gamma}} = A(p^1(Z,L),\cdots,p^N(Z,L),L^{11},\cdots,L^{M_NN},Z)$$

which implies that

$$\underbrace{\frac{\partial p^n}{\partial L^{ik}}(L_{ss})}_{D_{n,ik}} = \sum_h \underbrace{\frac{\partial A^n}{\partial p^h}}_{E_{n,h}} \underbrace{\frac{\partial p^h}{\partial L^{ik}}}_{D_{h,ik}} + \underbrace{\frac{\partial A^n}{\partial L^{ik}}}_{F_{n,ik}}$$

$$\underbrace{\frac{\partial p^n}{\partial Z^k}}_{D^z_{n,k}} = \sum_h \underbrace{\frac{\partial A^n}{\partial p^h}}_{E_{n,h}} \underbrace{\frac{\partial p^h}{\partial Z^k}}_{D^z_{h,k}} + \underbrace{\frac{\partial A^n}{\partial Z^k}}_{I^z_{n,k}}$$

where we can write out E, F, and I^z.

$$E_{n,k} = \frac{\chi^n Z^k \sum_{i\in\mathcal{M}_k} B^{ik}(L^{ik})^{1-\gamma}}{Z^n \sum_{j\in\mathcal{M}_n} B^{jn}(L^{jn})^{1-\gamma}}$$

$$F_{n,ik} = \begin{cases} \frac{\chi^n(1-\gamma)p^k Z^k B^{ik}(L^{ik})^{-\gamma}}{Z^n \sum_{j\in\mathcal{M}_n} B^{jn}(L^{jn})^{1-\gamma}} & \text{if } k \neq n \\ \frac{\chi^n(1-\gamma)p^n Z^n B^{jn}(L^{jn})^{-\gamma}}{Z^n \sum_{j\in\mathcal{M}_n} B^{jn}(L^{jn})^{1-\gamma}} - \frac{p^n(1-\gamma)B^{in}(L^{in}_t)^{-\gamma}}{\sum_{j\in\mathcal{M}_n} B^{jn}(L^{jn})^{1-\gamma}} & \text{if } k = n \end{cases}$$

and

$$I^z = \begin{cases} \frac{\chi^n p^k \sum_{i\in\mathcal{M}_k} B^{ik}(L^{ik})^{1-\gamma}}{Z^n \sum_{j\in\mathcal{M}_n} B^{jn}(L^{jn})^{1-\gamma}} & \text{if } k \neq n \\ \frac{\chi^n p^n \sum_{j\in\mathcal{M}_n} B^{jn}(L^{jn})^{1-\gamma}}{Z^n \sum_{j\in\mathcal{M}_n} B^{jn}(L^{jn})^{1-\gamma}} - \frac{p^n}{Z^n} & \text{if } k = n \end{cases}$$

So $D = (Id - E)^{-1}F$ and $D^z = (Id - E)^{-1}I^z$. Now we write the wage equation (after taking into account the proportional transfer) as:

$$\tilde{w}^{jn}_t = p^n_t B^{jn} Z^n_t (L^{jn}_t)^{-\gamma} = W(p^n(Z, L), L^{jn}, Z^n)$$

where $\tilde{w}^{jn}_t = \frac{1}{1-\gamma} w^{jn}_t$. This implies that:

$$\underbrace{\frac{\partial \tilde{w}^{jn}}{\partial L^{ik}}(L)}_{J_{jn,ik}} = \underbrace{\frac{\partial W^{jn}}{\partial p^h}}_{K_{jn,h}} \underbrace{\frac{\partial p^h}{\partial L^{ik}}}_{D_{h,ik}} + \underbrace{\frac{\partial W^{jn}}{\partial L^{ik}}}_{N_{jn,ik}}$$

$$\underbrace{\frac{\partial \tilde{w}^{jn}}{\partial Z^k}}_{J^z_{jn,k}} = \underbrace{\frac{\partial W^{jn}}{\partial p^n}}_{K_{jn,n}} \underbrace{\frac{\partial p^n}{\partial Z^k}}_{D^z_{n,k}} + \underbrace{\frac{\partial W^{jn}}{\partial Z^k}}_{N^z_{jn,k}}$$

where

$$K_{jn,k} = \begin{cases} 0 & \text{if } k \neq n \\ B^{jn} Z^n (L^{jn})^{-\gamma} & \text{if } k = n \end{cases}$$

$$N_{jn,ik} = \begin{cases} 0 & \text{if } ik \neq jn \\ -\gamma \tilde{w}^{jn}/L^{jn} & \text{if } ik = jn \end{cases}, \quad N^z_{jn,k} = \begin{cases} 0 & \text{if } k \neq jn \\ \tilde{w}^{jn}/Z^n & \text{if } ik = jn \end{cases}$$

and D and D^z are calculated previously.

The price index is given by:

$$P_t = \Pi_{j,n}\Big[p_t^n/\chi^n\Big]^{\chi^n}$$

The flow payoffs can be written, to first order, as,

$$\begin{aligned}\frac{u_t^{jn} - u_{ss}^{jn}}{\epsilon} =& u'(c_{ss}^{jn})\Big[\frac{1}{P_{ss}}(\sum_{i,k}\frac{\partial\tilde{w}^{jn}}{\partial L^{ik}}l^{ik} + \frac{\partial\tilde{w}^{jn}}{\partial Z^k}\delta^k Z^k) - \frac{w_{ss}^{jn}}{P_{ss}^2}(\sum_{i,k}\frac{\partial P}{\partial L^{ik}}l^{ik} + \frac{\partial P}{\partial Z^k}\delta^k Z^k)\Big] \\ =& u'(c_{ss}^{jn})\Big[\frac{1}{P_{ss}}(\sum_{i,k}\frac{\partial\tilde{w}^{jn}}{\partial L^{ik}}l^{ik} + \frac{\partial\tilde{w}^{jn}}{\partial Z^k}\delta^k Z^k)\Big]\end{aligned}$$

where we normalize the price index P to 1. In matrix format, we can write:

$$\epsilon^{-1}\Big(u_t - u_{ss}\Big) = \bar{\omega}z + \bar{v}n$$

where $\bar{v}$ and $\bar{\omega}$ represents the matrix:

$$\bar{v} = \frac{1}{P_{ss}}diag\big(u'(c_{ss})\big)J\bar{Q}$$

$$\bar{\omega} = \frac{1}{P_{ss}}diag\big(u'(c_{ss})\big)\bar{J}^z\bar{Z}$$

We also denote:

$$\bar{J}^z = \begin{bmatrix} J^z_{11,1}\cdots J^z_{11,1} & J^z_{11,2}\cdots J^z_{11,2} & \cdots & J^z_{11,N}\cdots J^z_{11,N} \\ J^z_{21,1}\cdots J^z_{21,1} & J^z_{21,2}\cdots J^z_{21,2} & \cdots & J^z_{21,N}\cdots \mu_t^{21,N} \\ \vdots & \ddots & \ddots & \vdots \\ J^z_{M_NN,1}\cdots J^z_{M_NN,1} & J^z_{M_NN,2}\cdots J^z_{M_NN,2} & \cdots & J^z_{M_NN,N}\cdots J^z_{M_NN,N} \end{bmatrix}$$

Finally, we denote:

$$\bar{Z} = [\delta^1 Z^1, 0, \cdots, 0, \delta^2 Z^2, 0, \cdots, 0, \cdots, \delta^N Z^N, 0, \cdots, 0]'$$

D.2.2 Continuation value from job switching

Denote by L the steady-state matrix of labor transition. In particular:

$$L = \phi(\mu - Id)$$

The continuation value from job switching becomes:

$$\frac{\mathcal{L}[V] - \mathcal{L}[V^{SS}]}{\epsilon} = Lvn + L\omega z$$

D.2.3 Continuation value from changes in worker distribution

Denote by L the steady-state matrix of labor distribution. The continuation value from job switching becomes:

$$\frac{\mathcal{L}[V] - \mathcal{L}[V^{SS}]}{\epsilon} = Lvn + Lv_l l + L\omega z$$

D.2.4 Continuation value from changes in worker distribution

The labor transition can be written as:

$$\mu_t^{ik,jn} = \Omega^{ik,jn}(\mu_t, L_t, z_t, V_t) =$$
$$\frac{\exp\left(V_t^{jn} - \hat{B}_t^{jn,ik} - (1-\alpha_1 l_t^{jn,ik})\bar{\kappa}^{ik,jn}\right)^{\frac{1}{\nu\zeta}} \exp\left(\zeta S_t^{ik,n} + \frac{1-\beta_0 l_t^{n,ik}}{\nu(\rho+\phi)}(\bar{z} - \log(Z_t^n)) - \frac{1}{\nu}(1-\alpha_0 l_t^{n,ik})\bar{\kappa}^{k,n}\right)}{\left[\sum_{r\in\mathcal{M}_n} \exp\left(V_t^{rn} - \hat{B}_t^{rn,ik} - (1-\alpha_1 l_t^{rn,ik})\bar{\kappa}^{ik,rn}\right)^{\frac{1}{\nu\zeta}}\right] \sum_{h\in\mathcal{N}} \exp\left(\zeta S_t^{ik,h} + \frac{1-\beta_0 l_t^{h,ik}}{\nu(\rho+\phi)}(\bar{z} - \log(Z_t^h)) - \frac{1}{\nu}(1-\alpha_0 l_t^{h,ik})\bar{\kappa}^{k,h}\right)} \tag{D.1}$$

where

$$\hat{B}_t^{jn,ik} = \begin{cases} \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{ik}) & \text{if } jn \neq ik \\ 0 & \text{if } jn = ik \end{cases}$$

$$S_t^{ik,h} = \log\left[\sum_{d\in\mathcal{M}_h} \exp\left(\frac{1}{\nu\zeta}\left(V_t^{dh} - \frac{1-\beta_1 l_t^{h,ik}}{\rho+\phi}\log(B^{dh}) - \left(1-\alpha_1 l_t^{dh,ik}\right)\bar{\kappa}^{ik,dh}\right)\right)\right]$$

$$l_t^{n,ik} = \sum_{r\in\mathcal{M}_n} \frac{\mu_t^{rn,ik} L_t^{rn}}{L_t^{ik}}, \quad l_t^{jn,ik} = \frac{\mu_t^{jn,ik} L_t^{jn}}{L_t^{ik}}$$

Taking the total derivative of equation (D.1) with respect to V^{dh} yields:

$$\underbrace{\frac{\partial \mu^{ik,jn}}{\partial V^{dh}}}_{R^{dh}_{ikjn,1}} = \sum_{m,s,l,q} \underbrace{\frac{\partial \mu^{ik,jn}}{\partial \mu^{ms,xq}}}_{T_{ikjn,msxq}} \underbrace{\frac{\partial \mu^{ms,xq}}{\partial V^{dh}}}_{R^{dh}_{msxq,1}} + \underbrace{\frac{\partial \Omega^{ik,jn}}{\partial V^{dh}}}_{\Omega^{dh}_{ikjn,1}} \tag{D.2}$$

R^{dh} is the column vector of the length $\tilde{N}^2$, where $\tilde{N} = \sum_{s=1}^{N} M_s$ represents the number of firms in the economy:

$$\begin{aligned} R^{dh} = \Big[& \frac{\partial \mu_t^{11,11}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{M_1 1,11}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{1N,11}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{M_N N,11}}{\partial V^{dh}}, \\ & \frac{\partial \mu_t^{11,21}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{M_1 1,21}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{1N,21}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{M_N N,21}}{\partial V^{dh}}, \\ & \dots \\ & \frac{\partial \mu_t^{11,M_N N}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{M_1 1,M_N N}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{1N,M_N N}}{\partial V^{dh}}, \dots, \frac{\partial \mu_t^{M_N N,M_N N}}{\partial V^{dh}} \Big]' \end{aligned}$$

and $R^{dh}_{ikjn,1}$ represents the $(ik + (jn-1)\times\tilde{N})$-th entry of the vector K^{dh}.

T is an $\tilde{N}^2$-by-$\tilde{N}^2$ matrix, for which we can calculate each entry:

$$\frac{\partial \mu^{ik,jn}}{\partial \mu^{ms,xq}} =$$

$$\begin{cases} 0 & \text{if } xq \neq ik \\ -\frac{\mu^{ik,jn}\mu^{ik,s}}{\nu}\left[\alpha_1 \mu^{ik,ms|s} + \sum_{d\in\mathcal{M}_s}\left(\frac{\beta_1 \log(B^{ds})}{\rho+\phi}\right)\mu^{ik,ds|s} + \left(\frac{\beta_0\left(\log(Z^s)-\bar{z}\right)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,s}\right)\right]\frac{L^{ms}}{L^{ik}} & \text{if } m\neq j,\ s\neq n, \text{ and } xq = ik \\ \frac{\mu^{ik,jn}}{\nu}\left[\frac{1}{\zeta}\frac{\beta_1}{\rho+\phi}\log(B^{jn}) + (1-\mu^{ik,n})\left(\frac{\beta_0\left(\log(Z^n)-\bar{z}\right)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,n}\right)\right. & \\ \left. +\left(1-\frac{1}{\zeta}-\mu^{ik,n}\right)\left(\alpha_1\mu^{ik,mn|n} + \sum_{r\in\mathcal{M}_n}\mathbb{1}(rn\neq jn)\left(\frac{\beta_1\log(B^{rn})}{\rho+\phi}\right)\mu^{ik,rn|n}\right)\right]\frac{L^{mn}}{L^{ik}} & \text{if } m\neq j,\ s=n \text{ and } xq=ik \\ \frac{\mu^{ik,jn}}{\nu}\left[\frac{1}{\zeta}\left(\frac{\beta_1}{\rho+\phi}\log(B^{jn})+\alpha_1\right) + (1-\mu^{ik,n})\left(\frac{\beta_0\left(\log(Z^n)-\bar{z}\right)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,n}\right)\right. & \\ \left. +\left(1-\frac{1}{\zeta}-\mu^{ik,n}\right)\left(\alpha_1\mu^{ik,jn|n} + \sum_{r\in\mathcal{M}_n}\mathbb{1}(rn\neq jn)\left(\frac{\beta_1\log(B^{rn})}{\rho+\phi}\right)\mu^{ik,rn|n}\right)\right]\frac{L^{jn}}{L^{ik}} & \text{if } ms=jn \text{ and } xq=ik \end{cases}$$

We can also calculate the second term in (D.2):

$$\Omega^{dh}_{ikjn} = \frac{\partial \Omega^{ik,jn}}{\partial V^{dh}} = \begin{cases} -\frac{1}{\nu}\mu^{ik,jn}\mu^{ik,dh} & \text{if } j\neq d \text{ and } n\neq h \\ \frac{1}{\nu}(1-\frac{1}{\zeta})\mu^{ik,jn}\mu^{ik,dn|n} - \frac{1}{\nu}\mu^{ik,jn}\mu^{ik,dn} & \text{if } j\neq d \text{ and } n=h \\ \frac{1}{\nu}\mu^{ik,jn}(\frac{1}{\zeta}-\mu^{ik,jn}) + \frac{1}{\nu}(1-\frac{1}{\zeta})\mu^{ik,jn}\mu^{ik,jn|n} & \text{if } j=d \text{ and } n=h \end{cases}$$

Then, we vertically stack all the vector R's and Ω's to be single vectors of length $\tilde{N}^3$:

$$\bar{R} = \begin{bmatrix} R^{11} \\ R^{21} \\ \vdots \\ R^{M_N M_N} \end{bmatrix},\quad \bar{\Omega} = \begin{bmatrix} \Omega^{11} \\ \Omega^{21} \\ \vdots \\ \Omega^{M_N M_N} \end{bmatrix}$$

Additionally, we stack all the T's to form a block diagonal matrix of size $\tilde{N}^3$-by-$\tilde{N}^3$:

$$\bar{T} = \begin{bmatrix} T & & & \\ & T & & \\ & & \ddots & \\ & & & T \end{bmatrix}$$

Then the system of equations can be represented as:

$$\bar{R} = \bar{T}\bar{R} + \bar{\Omega} \quad\Rightarrow\quad \bar{R} = (Id - \bar{T})^{-1}\bar{\Omega}$$

In addition, note that:

$$\underbrace{\frac{\partial \mu^{ik,jn}}{\partial L^{dh}}}_{R^{dh,L}_{ikjn,1}} = \sum_{m,s,l,q}\underbrace{\frac{\partial \mu^{ik,jn}}{\partial \mu^{ms,xq}}}_{T_{ikjn,msxq}}\underbrace{\frac{\partial \mu^{ms,xq}}{\partial L^{dh}}}_{R^{dh,L}_{msxq,1}} + \underbrace{\frac{\partial \Omega^{ik,jn}}{\partial L^{dh}}}_{\Omega^{dh,L}_{ikjn,1}} \tag{D.3}$$

where

$$R^{dh,L} = \Big[\frac{\partial \mu_t^{11,11}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{M_1 1,11}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{1N,11}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{M_N N,11}}{\partial L^{dh}}$$
$$\frac{\partial \mu_t^{11,21}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{M_1 1,21}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{1N,21}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{M_N N,21}}{\partial L^{dh}}$$
$$\dots$$
$$\frac{\partial \mu_t^{11,M_N N}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{M_1 1,M_N N}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{1N,M_N N}}{\partial L^{dh}}, \dots, \frac{\partial \mu_t^{M_N N,M_N N}}{\partial L^{dh}}\Big]'$$

$$\Omega_{ikjn}^{dh,L} = \frac{\partial \Omega^{ik,jn}}{\partial L^{dh}} = -\sum_{m,s}\Big[\frac{\partial \Omega^{ik,jn}}{\partial l^{ms,dh}}\frac{\mu^{ms,dh}L^{ms}}{(L^{dh})^2}\Big] + \sum_{x,q}\Big[\frac{\partial \Omega^{ik,jn}}{\partial l^{dh,xq}}\frac{\mu^{dh,xq}}{L^{xq}}\Big]$$

where $\frac{\partial \mu^{ik,jn}}{\partial l^{ms,xq}}$ has a similar structure to $\frac{\partial \mu^{ik,jn}}{\partial \mu^{ms,xq}}$:

$$\frac{\partial \mu^{ik,jn}}{\partial l^{ms,xq}} =$$
$$\begin{cases} 0 & \text{if } xq \neq ik \\ -\frac{\mu^{ik,jn}\mu^{ik,s}}{\nu}\Big[\alpha_1 \mu^{ik,ms|s} + \sum_{d\in\mathcal{M}_s}\Big(\frac{\beta_1 \log(B^{ds})}{\rho+\phi}\Big)\mu^{ik,ds|s} + \Big(\frac{\beta_0\big(\log(Z^s)-\bar{z}\big)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,s}\Big)\Big] & \text{if } m\neq j,\ s\neq n, \text{ and } xq = ik \\ \frac{\mu^{ik,jn}}{\nu}\Big[\frac{1}{\zeta}\frac{\beta_1}{\rho+\phi}\log(B^{jn}) + (1-\mu^{ik,n})\Big(\frac{\beta_0\big(\log(Z^n)-\bar{z}\big)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,n}\Big) & \\ +\Big(1-\frac{1}{\zeta}-\mu^{ik,n}\Big)\Big(\alpha_1\mu^{ik,mn|n} + \sum_{r\in\mathcal{M}_n}\mathbb{1}(rn\neq jn)\Big(\frac{\beta_1\log(B^{rn})}{\rho+\phi}\Big)\mu^{ik,rn|n}\Big)\Big] & \text{if } m\neq j,\ s=n \text{ and } xq=ik \\ \frac{\mu^{ik,jn}}{\nu}\Big[\frac{1}{\zeta}\Big(\frac{\beta_1}{\rho+\phi}\log(B^{jn})+\alpha_1\Big) + (1-\mu^{ik,n})\Big(\frac{\beta_0\big(\log(Z^n)-\bar{z}\big)}{\rho+\phi} + \alpha_0\bar{\kappa}^{k,n}\Big) & \\ +\Big(1-\frac{1}{\zeta}-\mu^{ik,n}\Big)\Big(\alpha_1\mu^{ik,jn|n} + \sum_{r\in\mathcal{M}_n}\mathbb{1}(rn\neq jn)\Big(\frac{\beta_1\log(B^{rn})}{\rho+\phi}\Big)\mu^{ik,rn|n}\Big)\Big] & \text{if } ms=jn \text{ and } xq=ik \end{cases}$$

After stacking all the R^L's and Ω^L, we can obtain $\bar{R}^L$ and $\bar{\Omega}^L$:

$$\bar{R}^L = \begin{bmatrix} R^{11,L} \\ R^{21,L} \\ \vdots \\ R^{M_N M_N,L} \end{bmatrix},\quad \bar{\Omega}^L = \begin{bmatrix} \Omega^{11,L} \\ \Omega^{21,L} \\ \vdots \\ \Omega^{M_N M_N,L} \end{bmatrix}$$

and we can obtain $\bar{R}^L$:

$$\bar{R}^L = (Id - \bar{T})^{-1}\bar{\Omega}^L$$

Similarly, taking the total derivative of equation (D.1) with respect to Z^h yields:

$$\underbrace{\frac{\partial \mu^{ik,jn}}{\partial Z^h}}_{R_{ikjn,1}^{h,z}} = \sum_{m,s,l,q}\underbrace{\frac{\partial \mu^{ik,jn}}{\partial \mu^{ms,lq}}}_{T_{ikjn,mslq}}\underbrace{\frac{\partial \mu^{ms,lq}}{\partial Z^h}}_{R_{mslq,1}^{h,z}} + \underbrace{\frac{\partial \Omega^{ik,jn}}{\partial Z^h}}_{\Omega_{ikjn,1}^{h,z}} \tag{D.4}$$

$$\frac{\partial \Omega^{ik,jn}}{\partial Z^h} = \begin{cases} \frac{1-\beta_0 l^{h,ik}}{\nu(\rho+\phi)}\mu^{ik,jn}\mu^{ik,h} & \text{if } n\neq h \\ \frac{1-\beta_0 l^{n,ik}}{\nu(\rho+\phi)}\mu^{ik,jn}(\mu^{ik,n}-1) & \text{if } n=h \end{cases}$$

$R^{h,z}$ is the column vector of the length $\tilde{N}^2$, where $\tilde{N} = \sum_{s=1}^{N} M_s$ represents the number of firms in the economy:

$$R^{h,z} = \Big[\frac{\partial \mu_t^{11,11}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{M_1 1,11}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{1N,11}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{M_N N,11}}{\partial Z^h}$$
$$\frac{\partial \mu_t^{11,21}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{M_1 1,21}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{1N,21}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{M_N N,21}}{\partial Z^h}$$
$$\cdots$$
$$\frac{\partial \mu_t^{11,M_N N}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{M_1 1,M_N N}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{1N,M_N N}}{\partial Z^h}, \cdots, \frac{\partial \mu_t^{M_N N,M_N N}}{\partial Z^h}\Big]'$$

We stack all the vector R^z's and Ω^z's to single vectors of length $\tilde{N}^2 \times N$:

$$\bar{R}^z = \begin{bmatrix} R^{1,z} \\ R^{2,z} \\ \vdots \\ R^{N,z} \end{bmatrix}, \quad \bar{\Omega}^z = \begin{bmatrix} \Omega^{1,z} \\ \Omega^{2,z} \\ \vdots \\ \Omega^{N,z} \end{bmatrix}$$

and we can obtain $\bar{R}^z$:

$$\bar{R}^z = (Id - \tilde{T})^{-1} \bar{\Omega}^z$$

where $\tilde{T}$ is a $\tilde{N}^2 \times N$-by- $\tilde{N}^2 \times N$ matrix with T's repeated on the diagonals.

To linearize the law of motion for worker distribution, we first reshape the $\bar{R}$ and $\bar{R}^z$ vectors to be matrices where the columns correspond to the dh dimension.

$$\tilde{R} = \begin{bmatrix} R^{11} & R^{21} & \cdots & R^{M_N M_N} \end{bmatrix}, \quad \tilde{R}^L = \begin{bmatrix} R^{11,L} & R^{21,L} & \cdots & R^{M_N M_N,L} \end{bmatrix}$$

$$\tilde{R}^z = \begin{bmatrix} R^{1,z} \cdots R^{1,z} & R^{2,z} \cdots R^{2,z} & \cdots & R^{M_N,z} \cdots R^{M_N M_N,z} \end{bmatrix}$$

where $R^{11}, \cdots, R^{M_N M_N}, R^{11,z}, R^{21,z}, \cdots, R^{M_N M_N,z}$ are all of $\tilde{N}^2$-by-1. We also define the $\tilde{N}$-by-$\tilde{N}^2$ matrix $\psi = Id \otimes l^*$. More specifically, ψ can be written as:

$$\psi = \begin{bmatrix} l_{11} \mathbb{1}_{1\times\tilde{N}} & 0 & 0 & \cdots & 0 \\ 0 & l_{21} \mathbb{1}_{1\times\tilde{N}} & 0 & \cdots & 0 \\ 0 & 0 & l_{31} \mathbb{1}_{1\times\tilde{N}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & l_{M_N N} \mathbb{1}_{1\times\tilde{N}} \end{bmatrix}$$

Note that:

$$[\psi \cdot \tilde{R}]_{jn,dh} = \sum_{i,k} \frac{\mu^{ik,jn}}{\partial V^{dh}} \cdot l^{ik}, \quad [\psi \cdot \tilde{R}^L]_{jn,dh} = \sum_{i,k} \frac{\mu^{ik,jn}}{\partial L^{dh}} \cdot l^{ik}$$

and for any $d \in \mathcal{M}_h$:

$$[\psi \cdot \tilde{R}^z]_{jn,dh} = \sum_{i,k} \frac{\mu^{ik,jn}}{\partial Z^h} \cdot l^{ik}$$

Now, note that the law of motion for worker distribution can be written as:

$$
\begin{aligned}
&L^*_{jn}(\mu, L + dL, Z, V + dV)[L_{ss}] \\
=&L^*_{jn}(\mu, L + dL, Z, V)[L_{ss}] + \phi \sum_{i,k} \sum_{d,h} \frac{\partial \mu^{ik,jn}}{\partial V^{dh}} dV^{dh} \cdot l^{ik} + \phi \sum_{i,k} \sum_{d,h} \frac{\mu^{ik,jn}}{\partial L^{dh}} dL^{dh} \cdot l^{ik} + \phi \sum_{i,k} \sum_{h} \frac{\partial \mu^{ik,jn}}{\partial Z^h} \delta^h Z^h z \cdot l^{ik} \\
=&L^*_{jn}(\mu, L + dL, Z, V)[L_{ss}] + \phi \Big\{ \Big[\psi \cdot \tilde{R} \cdot dV \Big]_{jn} + \Big[\psi \cdot \tilde{R}^L \cdot n \Big]_{jn} + \Big[\psi \cdot \tilde{R}^z \cdot \bar{Z} \cdot z \Big]_{jn} \Big\}
\end{aligned}
$$

In vector notation:

$$
\begin{aligned}
\epsilon^{-1} \Big(\sum_i \sum_k \frac{\partial V^{jn}}{\partial L^{ik}} (L^*(\mu, V) L) \Big)_{jn=11,21,\cdots,M_N M_n} &= vL^* n + v \underbrace{\phi \psi \tilde{R}}_{G} (vn + \omega z) + v \underbrace{\phi \psi \tilde{R}^L}_{Q} n + v \underbrace{\phi \psi \tilde{R}^z \bar{Z}}_{H} z \\
&= vL^* n + vG(vn + \omega z) + vQn + vHz
\end{aligned}
$$

D.2.5 FAME Equation

Collecting terms for v and ω, the FAME equations can be written as:

$$
\rho(vn + \omega z) = \bar{v} n + \bar{\omega} z + Lvn + L\omega z + vL^* n + vG(vn + \omega z) + vHz + \mathcal{A}(z)[\omega z]
$$

Collecting terms for v and ω, we can then obtain respective the deterministic and the stochastic FAME:

$$
\rho v = \bar{v} + Lv + vL^* + vGv + vQ
$$

$$
\rho \omega = \bar{\omega} + L\omega + vG\omega + vH + \mathcal{A}(z)[\omega z]
$$

where $\bar{v}, \bar{\omega}$, G and H are matrices defined previously.

D.3 Poof of Proposition 4

Total differentiation of aggregate welfare yields:

$$
d\bar{V} = \sum_{j \in \mathcal{M}_N} \sum_{n \in \mathcal{N}} \big[L^{jn} dV^{jn} + V^{jn} dL^{jn} \big] = \mathbb{E}_L[dV^{jn}] + Cov_L[\frac{dL^{jn}}{L^{jn}}, V^{jn}]
$$

where we normalize $\sum_{j,n} L^{jn} = 1$. We then note that:

$$
\begin{aligned}
\epsilon^{-1} \mathbb{E}_L[dV^{jn}] &= \sum_{jn} L^{jn} \big(\sum_{ik} v^{jn,ik} dL^{ik} + \omega^{jn} z \big) \\
&= \sum_{ik} \Big(\sum_{jn} L^{jn} v^{jn,ik} \Big) dL^{ik} + \sum_{jn} L^{jn} \omega^{jn} z \\
&= \mathbb{E}_L \Big[\epsilon^{v_L}_{ik} \frac{dL^{ik}}{L^{ik}} \Big] + \mathbb{E}_L[\omega^{jn} z]
\end{aligned}
$$

where we denote $\epsilon_{ik}^{v^L} = \sum_{jn} L^{jn} v^{jn,ik}$. Note that:

$$\mathbb{E}_L\Big[\epsilon_{ik}^{v^L} \frac{dL^{ik}}{L^{ik}}\Big] = Cov_L\Big[\epsilon_{ik}^{v^L}, \frac{dL^{ik}}{L^{ik}}\Big]$$

which means:

$$d\bar{V} = \mathbb{E}_L[\epsilon\omega^{jn}z] + Cov_L\Big[\frac{\epsilon dL^{jn}}{L^{jn}}, V^{jn}\Big] + Cov_L\Big[\epsilon_{jn}^{v^L}, \frac{\epsilon dL^{jn}}{L^{jn}}\Big]$$

E Model Solution and Estimation

E.1 Solving for the Stationary Equilibrium

Denote the optimal firm choice by firm i^* in sector k^*. Note that we now can rewrite the HJB equation for workers' problem:

$$\begin{aligned}
&(\rho+\phi)V^{jn} = u(c^{jn}) + \\
&\phi\sum_k \mathbb{P}(k=k^*)\times\int\Big\{\Big[\sum_i \mathbb{P}(i=i^*|k=k^*)\times\int\Big(V^{ik} - \frac{1-\beta_1 l^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l^{ik,jn})\bar{\kappa}^{jn,ik} + \nu\zeta\epsilon_1^{ik}\Big)dF(\epsilon_1^{ik}|i=i^*,k=k^*)\Big] \\
&+\frac{1-\beta_0 l^{k,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z^k)\Big) - (1-\alpha_0 l^{k,jn})\bar{\kappa}^{n,k} + \nu\epsilon_0^k\Big\}dF(\epsilon_0^k|k=k^*)
\end{aligned}$$

We then define the scheme, denoting by subscript ι the number of iteration:

$$\begin{aligned}
&(\rho+\phi)V_{\iota+1}^{jn} = u_\iota(c^{jn}) + \phi\sum_k \mathbb{P}_\iota(k=k^*) \\
&\times\int\Big\{\Big[\sum_i \mathbb{P}_\iota(i=i^*|k=k^*)\times\int\Big(V_{\iota+1}^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_\iota^{ik,jn})\bar{\kappa}^{jn,ik} + \nu\zeta\epsilon_1^{ik}\Big)dF_\iota(\epsilon_1^{ik}|i=i^*,k=k^*)\Big] \\
&+\frac{1-\beta_0 l_\iota^{k,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z^k)\Big) - (1-\alpha_0 l_\iota^{k,jn})\bar{\kappa}^{n,k} + \nu\epsilon_0^k\Big\}dF_\iota(\epsilon_0^k|k=k^*)
\end{aligned} \tag{E.1}$$

where the probabilities $\mathbb{P}_\iota(k=k^*), \mathbb{P}_\iota(i=i^*|k=k^*)$ and the flows $l_\iota^{k,jn}$ and $l_\iota^{ik,jn}$ all depend on the value obtained in the ιth iteration V_ι, whereas the value functions $V_{\iota+1}$ are all from the $\iota+1$-th iteration. We also take note that:

$$\begin{aligned}
&\int(V_\iota^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_\iota^{ik,jn})\bar{\kappa}^{jn,ik} + \nu\zeta\epsilon_1^{ik})dF_\iota(\epsilon_1^{ik}|i=i^*,k=k^*) \sim \\
&= \nu\zeta\log\sum_{r\in\mathcal{M}_k}\exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{rk} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_\iota^{rk,jn})\bar{\kappa}^{jn,rk}\Big)\Big]
\end{aligned}$$

Hence, the term within the square bracket in equation (E.1) can be written as:

$$
\begin{aligned}
&\sum_{i\in\mathcal{M}_k} \mu_t^{jn,ik|k} \int \Big(V_{\iota+1}^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_\iota^{ik,jn})\bar{\kappa}^{jn,ik} + \nu\zeta\epsilon_1^{ik}\Big) dF_\iota(\epsilon_1^{ik}|i=i^*,k=k^*) \\
&= \sum_{i\in\mathcal{M}_k} \mu_t^{jn,ik|k}\Big[(V_{\iota+1}^{ik} - V_\iota^{ik}) + \int \Big(V_\iota^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_\iota^{ik,jn})\bar{\kappa}^{jn,ik} + \nu\zeta\epsilon_1^{ik}\Big) dF_\iota(\epsilon_1^{ik}|i=i^*,k=k^*)\Big] \\
&= \sum_{i\in\mathcal{M}_k} \mu_t^{jn,ik|k} V_{\iota+1}^{ik} + \nu\zeta \sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k} \log \sum_{r\in\mathcal{M}_k} \exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{rk} - V_\iota^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_\iota^{rk,jn})\bar{\kappa}^{jn,rk}\Big)\Big]
\end{aligned}
$$

The first equation is obtained by subtracting and then adding back V_ι^{ik} from the ι-th iteration. The second equation uses the property for extreme value distributions we wrote down just above. Now we note that, using again the property of Gumbel distribution:

$$
\begin{aligned}
&\int \Big\{ \sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k} V_\iota^{ik} + \nu\zeta \sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k} \log \sum_{r\in\mathcal{M}_k} \exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{rk} - V_\iota^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_\iota^{rk,jn})\bar{\kappa}^{jn,rk}\Big)\Big] \\
&+ \frac{1-\beta_0 l_\iota^{k,jn}}{\rho+\phi}\Big(\bar{z} - \log(Z^k)\Big) - (1-\alpha_0 l_\iota^{k,jn})\bar{\kappa}^{n,k} + \nu\epsilon_0^k\Big\} dF_\iota(\epsilon_0^k|k=k^*) = \\
&\nu \log \sum_{h\in\mathcal{N}} \exp\Big[\frac{1}{\nu}\Big(\sum_{d\in\mathcal{M}_h} \mu_\iota^{jn,dh|h} V_\iota^{dh} + \nu\zeta \sum_{d\in\mathcal{M}_h} \mu_\iota^{jn,dh|h} \log \sum_{s\in\mathcal{M}_h} \exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{sh} - V_\iota^{dh} - \frac{1-\beta_1 l_\iota^{h,jn}}{\rho+\phi}\log(B^{sh}) - (1-\alpha_1 l_\iota^{sh,jn})\bar{\kappa}^{jn,sh}\Big) \\
&+ \frac{1-\beta_0 l_\iota^{h,jn}}{\rho+\phi}\Big(\bar{z} - \log(Z^h)\Big) - (1-\alpha_0 l_\iota^{h,jn})\bar{\kappa}^{n,h}\Big)\Big]
\end{aligned}
$$

Then we can write the right-hand side of equation (E.1) (omitting the constant ϕ) as:

$$
\begin{aligned}
&\sum_k \mathbb{P}_\iota(k=k^*) \int \Big\{ \Big[\sum_i \mathbb{P}_\iota(i=i^*|k=k^*) \times \int \Big(V_{\iota+1}^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_\iota^{ik,jn})\bar{\kappa}^{jn,ik} + \nu\zeta\epsilon_1^{ik}\Big) dF_\iota(\epsilon_1^{ik}|i=i^*,k=k^*)\Big] \\
&\quad + \frac{1-\beta_0 l_\iota^{k,jn}}{\rho+\phi}\Big(\bar{z} - \log(Z^k)\Big) - (1-\alpha_0 l_\iota^{k,jn})\bar{\kappa}^{n,k} + \nu\epsilon_0^k\Big\} dF_\iota(\epsilon_0^k|k=k^*) \\
&= \sum_k \mathbb{P}_\iota(k=k^*) \times \int \Big\{ \Big[\Big[\sum_{i\in\mathcal{M}_k} \mu_t^{jn,ik|k} V_{\iota+1}^{ik} + \nu\zeta \sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k} \log \sum_{r\in\mathcal{M}_k} \exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{rk} - V_\iota^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{rk}) - \\
&\quad (1-\alpha_1 l_\iota^{rk,jn})\bar{\kappa}^{jn,rk}\Big)\Big]\Big] + \frac{1-\beta_0 l_\iota^{k,jn}}{\rho+\phi}\Big(\bar{z} - \log(Z^k)\Big) - (1-\alpha_0 l_\iota^{k,jn})\bar{\kappa}^{n,k} + \nu\epsilon_0^k\Big\} dF_\iota(\epsilon_0^k|k=k^*) \\
&= \sum_k \mathbb{P}_\iota(k=k^*) \times \int \Big\{ \Big[\Big[\sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k}\Big(V_{\iota+1}^{ik} - V_\iota^{ik}\Big) + \sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k} V_\iota^{ik} + \nu\zeta \sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k} \log \sum_{r\in\mathcal{M}_k} \exp\Big[\\
&\quad \frac{1}{\nu\zeta}\Big(V_\iota^{rk} - V_\iota^{ik} - \frac{1-\beta_1 l_\iota^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_\iota^{rk,jn})\bar{\kappa}^{jn,rk}\Big)\Big]\Big] + \frac{1-\beta_0 l_\iota^{k,jn}}{\rho+\phi}\Big(\bar{z} - \log(Z^k)\Big) - (1-\alpha_0 l_\iota^{k,jn})\bar{\kappa}^{n,k} + \nu\epsilon_0^k\Big\} \\
&\quad dF_\iota(\epsilon_0^k|k=k^*) \\
&= \sum_k \mu_\iota^{jn,k}\Bigg(\sum_{i\in\mathcal{M}_k} \mu_\iota^{jn,ik|k}(V_{\iota+1}^{ik} - V_\iota^{ik}) + \nu\log\sum_{h\in\mathcal{N}} \exp\Big[\frac{1}{\nu}\Big(\sum_{d\in\mathcal{M}_h} \mu_\iota^{jn,dh|h} V_\iota^{dh} + \nu\zeta \sum_{d\in\mathcal{M}_h} \mu_\iota^{jn,dh|h} \log \\
&\quad \sum_{s\in\mathcal{M}_h} \exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{sh} - V_\iota^{dh} - \frac{1-\beta_1 l_\iota^{h,jn}}{\rho+\phi}\log(B^{sh}) - (1-\alpha_1 l_\iota^{sh,jn})\bar{\kappa}^{jn,sh}\Big)\Big] + \frac{1-\beta_0 l_\iota^{h,jn}}{\rho+\phi}\Big(\bar{z} - \log(Z^h)\Big) - (1-\alpha_0 l_\iota^{h,jn})\bar{\kappa}^{n,h}\Big)\Big]\Bigg)
\end{aligned}
$$

$$=\sum_k \mu_\iota^{jn,k}\Bigg(\sum_{i\in\mathcal{M}_k}\mu_\iota^{jn,ik|k}V_{\iota+1}^{ik}+\nu\log\sum_{h\in\mathcal{N}}\exp\Big[\frac{1}{\nu}\Big(\sum_{d\in\mathcal{M}_h}\mu_\iota^{jn,dh|h}V_\iota^{dh}-\sum_{i\in\mathcal{M}_k}\mu_\iota^{jn,ik|k}V_\iota^{ik}+\nu\zeta\sum_{d\in\mathcal{M}_h}\mu_\iota^{jn,dh|h}\log$$

$$\sum_{s\in\mathcal{M}_h}\exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{sh}-V_\iota^{dh}-\frac{1-\beta_1 l_\iota^{h,jn}}{\rho+\phi}\log(B^{sh})-(1-\alpha_1 l_\iota^{sh,jn})\bar{\kappa}^{jn,sh}\Big)\Big]+\frac{1-\beta_0 l_\iota^{h,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z^h)\Big)-(1-\alpha_0 l_\iota^{h,jn})\bar{\kappa}^{n,h}\Big)\Big]\Bigg)$$

So we obtain, after putting all terms from the ι-th iteration to the left-hand side:

$$(\rho+\phi)V_{\iota+1}^{jn}-\phi\sum_k\mu_\iota^{jn,k}\Big(\sum_{i\in\mathcal{M}_k}\mu_\iota^{jn,ik|k}V_{\iota+1}^{ik}\Big)$$

$$=u(c^{jn})+\phi\nu\sum_k\mu_\iota^{jn,k}\log\sum_{h\in\mathcal{N}}\exp\Big[\frac{1}{\nu}\Big(\sum_{d\in\mathcal{M}_h}\mu_\iota^{jn,dh|h}V_\iota^{dh}-\sum_{i\in\mathcal{M}_k}\mu_\iota^{jn,ik|k}V_\iota^{ik}+\nu\zeta\sum_{d\in\mathcal{M}_h}\mu_\iota^{jn,dh|h}\log$$

$$\sum_{s\in\mathcal{M}_h}\exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{sh}-V_\iota^{dh}-\frac{1-\beta_1 l_\iota^{h,jn}}{\rho+\phi}\log(B^{sh})-(1-\alpha_1 l_\iota^{sh,jn})\bar{\kappa}^{jn,sh}\Big)\Big]+\frac{1-\beta_0 l_\iota^{h,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z^h)\Big)-(1-\alpha_0 l_\iota^{h,jn})\bar{\kappa}^{n,h}\Big)\Big]\Bigg)$$

which can be written in matrix format:

$$[(\rho+\phi)Id-\mu_\iota]V_{\iota+1}=u+\phi\nu\sum_k\mu_\iota^{jn,k}\log\sum_{h\in\mathcal{N}}\exp\Big[\frac{1}{\nu}\Big(\sum_{d\in\mathcal{M}_h}\mu_\iota^{jn,dh|h}V_\iota^{dh}-\sum_{i\in\mathcal{M}_k}\mu_\iota^{jn,ik|k}V_\iota^{ik}+\nu\zeta\sum_{d\in\mathcal{M}_h}\mu_\iota^{jn,dh|h}\log$$

$$\sum_{s\in\mathcal{M}_h}\exp\Big[\frac{1}{\nu\zeta}\Big(V_\iota^{sh}-V_\iota^{dh}-\frac{1-\beta_1 l_\iota^{h,jn}}{\rho+\phi}\log(B^{sh})-(1-\alpha_1 l_\iota^{sh,jn})\bar{\kappa}^{jn,sh}\Big)\Big]+\frac{1-\beta_0 l_\iota^{h,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z^h)\Big)-(1-\alpha_0 l_\iota^{h,jn})\bar{\kappa}^{n,h}\Big)\Big]\Bigg) \tag{E.2}$$

where μ_ι is the firm-to-firm transition matrix. u is the vector contain the flow utility derived from working in each firm in the economy. Starting with initial guess V_0, we iterate to obtain $V_{\iota+1}$ from V_ι until convergence.

E.2 Job Switching Elasticity

Recall that the HJB equation for an individual employed in jn at time t can be written as:

$$\begin{aligned}\rho V^{jn} =&u(c_t^{jn})+\mathcal{L}[V]+\mathbb{E}[\frac{dV_t^{jn}}{dt}],\\ \mathcal{L}[V]\equiv&\phi\Bigg\{\nu\log\sum_{h\in\mathcal{N}}\exp\Bigg(\zeta\log\sum_{d\in\mathcal{M}_h}\exp\Big[\frac{1}{\nu\zeta}\Big(V_t^{dh}-\hat{B}_t^{jn,dh}-(1-\alpha_1 l_t^{dh,jn})\bar{\kappa}^{jn,dh}\Big)\Big]+\\ &\frac{1-\beta_0 l_t^{k,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z_t^h)\Big)-(1-\alpha_0 l_t^{h,jn})\bar{\kappa}^{n,h}\Bigg)-V_t^{jn}\Bigg\}\\ =&\phi\Bigg\{\nu\log\sum_{h\in\mathcal{N}}\exp\Big(\zeta S_t^{jn,h}+\frac{1-\beta_0 l_t^{h,jn}}{\rho+\phi}\Big(\bar{z}-\log(Z_t^h)\Big)-(1-\alpha_0 l_t^{h,jn})\bar{\kappa}^{n,h}\Big)-V_t^{jn}\Bigg\}\end{aligned}$$

Moreover, from equations (19) and (20), we know that:

$$\mu_t^{jn,n}=\frac{\exp\Big(\zeta S_t^{jn,n}+\frac{1-\beta_0 l_t^{n,jn}}{\nu(\rho+\phi)}(\bar{z}-\log(Z_t^n))\Big)}{\sum_{h\in\mathcal{N}}\exp\Big(\zeta S_t^{jn,h}+\frac{1-\beta_0 l_t^{h,jn}}{\nu(\rho+\phi)}(\bar{z}-\log(Z_t^h))-\frac{1}{\nu}(1-\alpha_0 l_t^{h,jn})\bar{\kappa}^{n,h}\Big)}$$

$$\mu_t^{jn,jn|n} = \frac{\exp\left(V_t^{jn} - (1-\alpha_1 l_t^{jn,jn})\bar{\kappa}^{jn,jn}\right)^{\frac{1}{\nu\zeta}}}{\sum_{r\in\mathcal{M}_n} \exp\left(V_t^{rn} - \frac{1-\beta_1 l_t^{n,jn}}{\rho+\phi}\log(B^{rn}) - (1-\alpha_1 l_t^{rn,jn})\bar{\kappa}^{jn,rn}\right)^{\frac{1}{\nu\zeta}}}$$

where

$$S_t^{jn,h} = \log\left[\sum_{d\in\mathcal{M}_h} \exp\left(\frac{1}{\nu\zeta}\left(V_t^{dh} - \hat{B}_t^{jn,dh} - \left(1-\alpha_1 l_t^{dh,jn}\right)\bar{\kappa}^{jn,dh}\right)\right)\right]$$

So we can write, by taking log on both sides of for equations (19) and (20):

$$\begin{aligned}
&-\nu\log\mu_t^{jn,n} \\
=&\nu\log\left[\sum_{h\in\mathcal{N}}\exp\left(\zeta S_t^{jn,h} + \frac{1-\beta_0 l_t^{h,jn}}{\nu(\rho+\phi)}(\bar{z}-\log(Z_t^h)) - \frac{1}{\nu}(1-\alpha_0 l_t^{h,jn})\bar{\kappa}^{n,h}\right)\right] - \nu\zeta S_t^{jn,n} - \frac{1-\beta_0 l_t^{n,jn}}{\rho+\phi}\left(\bar{z}-\log(Z_t^n)\right)
\end{aligned} \tag{E.3}$$

$$\begin{aligned}
&-\nu\zeta\log\mu_t^{jn,jn|n} \\
=&\nu\zeta\log\sum_{r\in\mathcal{M}_n}\exp\left(V_t^{rn} - \hat{B}^{jn,rn} - \left(1-\alpha_1 l_t^{rn,jn}\right)\right)^{\frac{1}{\nu\zeta}} - V_t^{jn} + \left(1-\alpha_1 l_t^{jn,jn}\right)\bar{\kappa}^{jn,jn} \\
=&\nu\zeta S_t^{jn,n} - V_t^{jn} + \left(1-\alpha_1 l_t^{jn,jn}\right)\bar{\kappa}^{jn,jn}
\end{aligned} \tag{E.4}$$

In addition, we can approximate $dV_t^{jn}/dt \approx V_t^{jn} - V_{t-1}^{jn}$ and $dV_t^{rn}/dt \approx V_t^{rn} - V_{t-1}^{rn}$ so that we have:

$$\begin{aligned}
&\frac{dV_t^{rn} - dV_t^{jn}}{dt} \approx (V_t^{rn} - V_t^{rn}) - (V_{t-1}^{jn} - V_{t-1}^{jn}) \\
=&\nu\zeta\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \frac{1-\beta_1 l_t^{n,jn}}{\rho+\phi}\log B^{rn} + \bar{\kappa}^{jn,rn} - \alpha_1 l_t^{rn,jn}\bar{\kappa}^{jn,rn} - \left(\nu\zeta\log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}} + \frac{1-\beta_1 l_{t-1}^{n,jn}}{\rho+\phi}\log B^{rn} + \bar{\kappa}^{jn,rn} - \alpha_1 l_{t-1}^{rn,jn}\bar{\kappa}^{jn,rn}\right) \\
=&\nu\zeta\left(\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} - \log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}}\right) - \frac{\beta_1(l_t^{n,jn} - l_{t-1}^{n,jn})}{\rho+\phi}\log B^{rn} - \alpha_1(l_t^{rn,jn} - l_{t-1}^{rn,jn})\bar{\kappa}^{jn,rn}
\end{aligned}$$

By combining (E.3) and (E.4), we can obtain:

$$\begin{aligned}
&\phi\left\{\nu\log\sum_{h\in\mathcal{N}}\exp\left(S_t^{jn,h} + \frac{1-\beta_0 l_t^{h,jn}}{\rho+\phi}\left(\bar{z}-\log(Z_t^h)\right) - (1-\alpha_0 l_t^{h,jn})\bar{\kappa}^{n,h}\right) - V_t^{jn}\right\} \\
=&\phi\left\{-\left(\nu\log\mu_t^{jn,n} + \nu\zeta\log\mu_t^{jn,jn|n}\right) + \frac{1-\beta_0 l_t^{n,jn}}{\rho+\phi}\left(\bar{z}-\log(Z_t^n)\right) - \left(1-\alpha_1 l_t^{jn,jn}\right)\bar{\kappa}^{jn,jn}\right\}
\end{aligned} \tag{E.5}$$

$$\begin{aligned}
&\phi\left\{\nu\log\sum_{h\in\mathcal{N}}\exp\left(S_t^{rn,h} + \frac{1-\beta_0 l_t^{h,rn}}{\rho+\phi}\left(\bar{z}-\log(Z_t^h)\right) - (1-\alpha_0 l_t^{h,rn})\bar{\kappa}^{n,h}\right) - V_t^{rn}\right\} \\
=&\phi\left\{-\left(\nu\log\mu_t^{rn,n} + \nu\zeta\log\mu_t^{rn,rn|n}\right) + \frac{1-\beta_0 l_t^{n,rn}}{\rho+\phi}\left(\bar{z}-\log(Z_t^n)\right) - \left(1-\alpha_1 l_t^{rn,rn}\right)\bar{\kappa}^{rn,rn}\right\}
\end{aligned} \tag{E.6}$$

Now we are ready to rewrite the difference in logged flows across two firms, in equation (E.7):

$$\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}}$$

$$
\begin{aligned}
=&\frac{1}{\nu\zeta}(V_t^{rn}-V_t^{jn})-\frac{1}{\nu\zeta}\frac{1-\beta_1 l_t^{n,jn}}{\rho+\phi}\log B^{rn}-\frac{1}{\nu\zeta}\bar{\kappa}^{jn,rn}+\frac{\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa}^{jn,rn}\\
=&\frac{1}{\rho\nu\zeta}\left[u(c_t^{rn})-u(c_t^{jn})-\frac{\phi\beta_0(l_t^{n,rn}-l_t^{n,jn})}{\rho+\phi}\Big(\bar{z}-\log(Z_t^n)\Big)+\mathbb{E}\Big[\frac{dV_t^{rn}-dV_t^{jn}}{dt}\Big]\right]\\
&-\frac{\phi}{\rho\zeta}\log\frac{\mu_t^{rn,n}}{\mu_t^{jn,n}}-\frac{\phi}{\rho}\log\frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}}-\frac{1}{\nu\zeta}\frac{1-\beta_1 l_t^{n,jn}}{\rho+\phi}\log B^{rn}-\frac{1}{\nu\zeta}\bar{\kappa}^{jn,rn}+\frac{\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa}^{jn,rn}\\
=&\frac{1}{\rho\nu\zeta}\left[u(c_t^{rn})-u(c_t^{jn})-\frac{\phi\beta_0(l_t^{n,rn}-l_t^{n,jn})}{\rho+\phi}\Big(\bar{z}-\log(Z_t^n)\Big)\right]+\frac{1}{\rho\nu\zeta}\mathbb{E}\Big[\nu\zeta\Big(\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}}-\log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}}\Big)-\frac{\beta_1(l_t^{n,jn}-l_{t-1}^{n,jn})}{\rho+\phi}\log B^{rn}\\
&-\alpha_1(l_t^{rn,jn}-l_{t-1}^{rn,jn})\bar{\kappa}^{jn,rn}\Big]-\frac{\phi}{\rho\zeta}\log\frac{\mu_t^{rn,n}}{\mu_t^{jn,n}}-\frac{\phi}{\rho}\log\frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}}-\frac{1}{\nu\zeta}\frac{1-\beta_1 l_t^{n,jn}}{\rho+\phi}\log B^{rn}-\frac{1}{\nu\zeta}\bar{\kappa}^{jn,rn}+\frac{\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa}^{jn,rn}\\
\Longrightarrow&(\rho-1)\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}}+\log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}}=\\
&\frac{1}{\nu\zeta}\log\frac{w_t^{rn}}{w_t^{jn}}-\frac{\phi}{\zeta}\log\frac{\mu_t^{rn,n}}{\mu_t^{jn,n}}-\phi\log\frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}}-\frac{\phi\beta_0(l_t^{n,rn}-l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\Big(\bar{z}_t-\log(Z_t^n)\Big)\\
&-\frac{\beta_1(l_t^{n,jn}-l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn}-\frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn}-l_{t-1}^{rn,jn})\bar{\kappa}^{jn,rn}-\frac{\rho(1-\beta_1 l_t^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn}-\frac{\rho}{\nu\zeta}\bar{\kappa}^{jn,rn}+\frac{\rho\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa}^{jn,rn}+\epsilon_t
\end{aligned}
$$

where ϵ_t represents the expectational error. The second equation is obtained by rearranging the HJB equation, the third equation is obtained by substituting equation (E.5) and (E.6) into the $\mathcal{L}[V]$ term of the HJB equation, and the final equation is obtained by substituting in the expressions of $u(c_t^{jn})$, $u(c_t^{rn})$, and rearranging the terms.

Rearranging terms, we write the estimating equation as:

$$
(\rho-1)\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}}+\log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}}+\frac{\phi}{\zeta}\log\frac{\mu_t^{rn,n}}{\mu_t^{jn,n}}=\frac{1}{\nu\zeta}\Big[\log\frac{w_t^{rn}}{w_t^{jn}}-\frac{\rho}{\rho+\phi}\log B^{rn}\Big]-\phi\log\frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}}+\mathcal{Z}_t+\epsilon_t \quad \text{(E.7)}
$$

where $\mathcal{Z}_t$ summarizes the coworker influences:

$$
\begin{aligned}
\mathcal{Z}_t=&-\frac{\phi\beta_0(l_t^{n,rn}-l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\Big(\bar{z}_t-\log(Z_t^n)\Big)\\
&-\frac{\beta_1(l_t^{n,jn}-l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn}-\frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn}-l_{t-1}^{rn,jn})\bar{\kappa}^{jn,rn}+\frac{\beta_1 l_t^{n,jn}}{(\rho+\phi)\nu\zeta}\log B^{rn}-\frac{\rho}{\nu\zeta}\bar{\kappa}^{jn,rn}+\frac{\rho\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa}^{jn,rn}
\end{aligned}
$$

E.3 Job Switching Costs and Coworker-related Parameters

We now outline the estimation procedures related to the coworker network as well as the value functions associated with working each firm at the steady state.

Recall that the sector- and firm-level flows are given by, $\forall ik\neq jn$

$$
\mu_t^{jn,k}=\frac{\exp\Big(\zeta S_t^{jn,k}+\frac{1-\beta_0 l_t^{k,jn}}{\nu(\rho+\phi)}(\bar{z}-\log(Z_t^k))-\frac{1}{\nu}(1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k}\Big)}{\sum_{h\in\mathcal{N}}\exp\Big(\zeta S_t^{jn,h}+\frac{1-\beta_0 l_t^{h,jn}}{\nu(\rho+\phi)}(\bar{z}-\log(Z_t^h))-\frac{1}{\nu}(1-\alpha_0 l_t^{h,jn})\kappa_t^{n,h}\Big)}
$$

$$\mu_t^{jn,ik|k} = \frac{\exp\left(V_t^{ik} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{ik}) - (1-\alpha_1 l_t^{ik,jn})\bar{\kappa}^{jn,ik}\right)^{\frac{1}{\nu\zeta}}}{\sum_{r\in\mathcal{M}_k}\exp\left(V_t^{rk} - \frac{1-\beta_1 l_t^{k,jn}}{\rho+\phi}\log(B^{rk}) - (1-\alpha_1 l_t^{rk,jn})\bar{\kappa}^{jn,rk}\right)^{\frac{1}{\nu\zeta}}}$$

Moreover, workers know perfectly the TFP of their own firm. This implies that we can compare the flows to two different sectors or to two different firms within the same sector:

$$\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} = \frac{1}{\nu\zeta}(V_t^{rn} - V_t^{jn}) - \frac{1}{\nu\zeta}\frac{1-\beta_1 l_t^{n,jn}}{\rho+\phi}\log B^{rn} - \frac{1}{\nu\zeta}\bar{\kappa}^{jn,rn} + \frac{\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa}^{jn,rn} \tag{E.7}$$

$$\log\frac{\mu_t^{jn,k}}{\mu_t^{jn,n}} = \zeta S_t^{jn,k} - \zeta S_t^{jn,n} - \frac{1}{\nu(\rho+\phi)}\left[(1-\beta_0 l_t^{k,jn})\log(Z_t^k) - (1-\beta_0 l_t^{n,jn})\log(Z_t^n)\right] - \frac{1}{\nu}\left[(1-\alpha_0 l_t^{k,jn})\bar{\kappa}^{n,k}\right] \tag{E.8}$$

where we normalize the common-component of the own-sector transition costs to be $\bar{\kappa}^{n,n} = 0$ in equation (E.8).

First, we can use equation (E.7) to write:

$$\begin{aligned}\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log\frac{\mu_t^{rn,jn|n}}{\mu_t^{rn,rn|n}} = &-\frac{1}{\nu\zeta(\rho+\phi)}(\log B^{rn} + \log B^{jn}) + \frac{\beta_1(l_t^{n,jn}\log B^{rn} + l_t^{n,rn}\log B^{jn})}{\nu\zeta(\rho+\phi)} - \frac{1}{\nu\zeta(\rho+\phi)}(\log B^{rn} + \log B^{jn}) \\ &- \frac{1}{\nu\zeta}(\bar{\kappa}^{jn,rn} + \bar{\kappa}^{rn,jn}) + \frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn}\bar{\kappa}^{jn,rn} + l_t^{jn,rn}\bar{\kappa}^{rn,jn})\end{aligned} \tag{E.9}$$

where the flows on the left-hand side are all observable from the data. Since we group actual firms in the data into "firm groups" based on their quality, we impose the assumption that the cross-firm transition costs:

$$\bar{\kappa}^{jn,ik} = \begin{cases}\bar{\kappa} & \text{if } i \neq j \\ 0 & \text{if } i = j\end{cases}$$

Meaning that the firm-level transition costs will be a constant $\bar{\kappa}$ for all job switchers that go to a firm belonging to a higher firm quality quartile in any sector, but 0 if they move into a firm within a group consisting of lower quality firms. With this, we writer write equation (E.9) as:

$$\begin{aligned}\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log\frac{\mu_t^{rn,jn|n}}{\mu_t^{rn,rn|n}} = &\frac{\beta_1}{\nu\zeta(\rho+\phi)}(l_t^{n,jn}\log B^{rn} + l_t^{n,rn}\log B^{jn}) \\ &- \frac{1}{\nu\zeta(\rho+\phi)}(\log B^{rn} + \log B^{jn}) + \frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn} + l_t^{jn,rn})\bar{\kappa} - \frac{2}{\nu\zeta}\bar{\kappa}\end{aligned} \tag{E.10}$$

And equation (E.7) as:

$$\begin{aligned}&(\rho-1)\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,jn|n}} = \\ &\frac{1}{\nu\zeta}\log\frac{w_t^{rn}}{w_t^{jn}} - \frac{\phi}{\zeta}\log\frac{\mu_t^{rn,n}}{\mu_t^{jn,n}} - \phi\log\frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}} - \frac{\phi\beta_0(l_t^{n,rn} - l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\left(\bar{z}_t - \log(Z_t^n)\right) \\ &- \frac{\beta_1(l_t^{n,jn} - l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn} - \frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn} - l_{t-1}^{rn,jn})\bar{\kappa} - \frac{\rho(1-\beta_1 l_t^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn} - \frac{\rho}{\nu\zeta}\bar{\kappa} + \frac{\rho\alpha_1}{\nu\zeta}l_t^{rn,jn}\bar{\kappa} + \epsilon_t\end{aligned} \tag{E.11}$$

Next, to recover the parameters governing sector-level transitions, we restrict to the steady state and resort to a two-step iterative algorithm. The algorithm is as follows. First, we given α_1, β_1 and $\bar{\kappa}^{n,k}$ for all sector pairs n, k, we guess the sector-level coworker-related parameters α_0, β_0. Second, given the guesses, we can use the algorithm in section E.1 to calculate the value functions associated with working at each firm, V^{ik}. We can also calculate the sector-level, the firm-level transition matrices, and the inclusive value, $S^{jn,k}$, of transitioning from each firm jn to each sector k. Third, with the inclusive value and the law of motion for labor know, we can derive from (E.8) that:

$$\log \frac{\mu_t^{jn,k}}{\mu_t^{jn,n}} + \log \frac{\mu_t^{ik,n}}{\mu_t^{ik,k}} =$$

$$\zeta(S_t^{jn,k} - S_t^{ik,k}) - \zeta(S_t^{jn,n} - S_t^{ik,n}) + \frac{\beta_0}{\nu(\rho+\phi)}\Big[(l_t^{k,jn} - l_t^{k,ik})\log(Z_t^k) - (l_t^{n,jn} - l_t^{n,ik})\log(Z_t^n)\Big] + \frac{\alpha_0}{\nu}\Big[l_t^{k,jn} + l_t^{n,ik}\Big]\bar{\kappa}^{n,k} - \frac{2}{\nu}\bar{\kappa}^{n,k} \tag{E.12}$$

where we impose the assumption of symmetry, so that $\bar{\kappa}^{n,k} = \bar{\kappa}^{k,n}$. which we use to recover α_0 and β_0 at the steady state.

E.4 Estimating $\nu, \alpha_1, \beta_1, \alpha_0, \beta_0$

We recover the parameters related to one's job choices in two steps. In the first step, we use data on bilateral flows within sector to recover the firm-level coworker-related parameters α_1 and β_1 together with the baseline firm-level transition cost $\bar{\kappa}$. Controlling for the firm-level coworker influences, we back out the job-switching elasticity ν using data comparing the size of unilateral flows with job stayers at each origin firm within each sector. Finally, we restrict to the steady state and recover the sector-level coworker network parameters, α_0 and β_0, and the baseline sector-level switching cost $\bar{\kappa}^{n,k}$.

Steps for Recovering $\nu, \phi, \bar{\kappa}, \alpha_1, \beta_1$

- Construct $y_1 = \log \frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log \frac{\mu_t^{rn,jn|n}}{\mu_t^{rn,rn|n}}$, $x_1 = l_t^{n,jn} log B^{rn} - l_t^{n,rn} \log B^{jn}$, $x_2 = l_t^{rn,jn} - l_t^{jn,rn}$ from the data. Guess a value of for the within-sector job-switching elasticity, $(\nu\zeta)^{old}$. Since we already set the values of ρ and ϕ, we can construct the left-hand side variable:

$$y_1^{bilateral} = y_1 - \frac{1}{(\nu\zeta)^{old}(\rho+\phi)}(\log B^{rn} + \log B^{jn})$$

- Estimate the regression:

$$y_1 = \alpha_1^{bilateal} x_1 + \alpha_2^{bilateral} x_2 + c^{bilateral}$$

  According to equation (E.10), we can obtain:

$$\frac{\beta_1}{\nu\zeta(\rho+\phi)} = \hat{\alpha}_1^{bilateral}, \quad \frac{\alpha_1}{\nu\zeta}\bar{\kappa} = \hat{\alpha}_2^{bilateral}$$

- Now we turn to equation (E.11), and construct:

$$network\_TFP = -\frac{\beta_1(l_t^{n,jn} - l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn} + \frac{\rho\beta_1 l_t^{n,jn}}{(\rho+\phi)\nu\zeta}\log B^{rn} = \hat{\alpha}_1^{bilateral}(l_t^{n,jn} - l_{t-1}^{n,jn})\log B^{rn} + \rho\hat{\alpha}_1^{bilateral} l_t^{n,jn}\log B^{rn}$$

$$network\_cost = -\frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn} - l_{t-1}^{rn,jn})\bar{\kappa} - \frac{\rho}{\nu\zeta}\bar{\kappa} + \frac{\rho\alpha_1}{\nu\zeta} l_t^{rn,jn}\bar{\kappa}$$

$$w\_diff = \log\frac{w_t^{rn}}{w_t^{jn}} - \frac{\rho}{\rho+\phi}\log B^{rn}, \quad sector\_network = \frac{\phi\beta_0(l_t^{n,rn} - l_t^{n,jn]})}{(\rho+\phi)\nu\zeta}(\bar{z} - \log(Z_t^n))$$

$$y_2 = (\rho-1)\log\frac{\mu_t^{jn,rn|n}}{\mu_t^{jn,jn|n}} + \log\frac{\mu_{t-1}^{jn,rn|n}}{\mu_{t-1}^{jn,rn|n}} + \phi\log\frac{\mu_t^{rn,rn|n}}{\mu_t^{jn,jn|n}} + \log\frac{\phi}{\zeta}\log\frac{\mu_t^{rn,n}}{\mu_t^{jn,n}} - network\_TFP - network\_cost$$

- Estimate the regression:

$$y_2 = \alpha_1^{unilateral} w\_diff + \alpha_3^{unilateral} sector\_network + c^{error}$$

  We can then obtain the implied within-sector switching elasticity with respect to wage differential $(\nu\zeta)^{new} = 1/\hat{\alpha}_1^{unilateral}$. Compare $(\nu\zeta)^{old}$ with $(\nu\zeta)^{new}$. If they are different, reset $(\nu\zeta)^{old} = (\nu\zeta)^{new}$ and repeat from the first step. Iterate on this process until the estimate for $\nu\zeta$ converges. We can then obtain:

$$\beta_1 = (\rho+\phi)\hat{\alpha}_1^{bilateral} * \nu\zeta, \quad \alpha_1 = \hat{\alpha}_2^{bilateral} * (\nu\zeta)/\bar{\kappa}$$

Setting α_1, β_1 or both to zero We investigate the implication of our model by shutting down either one or both of the role that one's firm-level coworker network plays, by setting α_1, β_1, or both to 0:

- **No coworker network** We set $\alpha_1 = 0$ and $\beta_1 = 0$, and obtain $\frac{1}{\nu\zeta}\bar{\kappa}$ from the constant term in the regression:

$$y_1 = \alpha_3^{bilateral'} + c^{bilateral'}$$

  We then estimate ϕ and $\nu\zeta$ similarly as above, after setting:

$$network\_TFP = 0, \quad network\_cost = -\frac{\rho}{\nu\zeta}\bar{\kappa}$$

- **No coworker influence on TFP beliefs** We set $\alpha_1 \neq 0$ and $\beta_1 = 0$. We run the regression:

$$y_1 = \alpha_2^{bilateral''} x_2 + \alpha_3^{bilateral''} x_3 + c^{bilateral''}$$

  and obtain $\alpha_1 = 2c^{bilateral''}/\alpha_2^{bilatera''}$. We then estimate ϕ and $\nu\zeta$ similarly as above, after setting:

$$network\_TFP = 0, \quad network\_cost = -\frac{\alpha_1}{\nu\zeta}(l_t^{rn,jn} - l_{t-1}^{rn,jn})\bar{\kappa} - \frac{\rho}{\nu\zeta}\bar{\kappa} + \frac{\rho\alpha_1}{\nu\zeta} l_t^{rn,jn}\bar{\kappa}$$

- **No coworker influence on adjustment costs** We set $\alpha_1 = 0$ and $\beta_1 \neq 0$. We run the regression:

$$y_1 = \alpha_1^{bilateral'''} x_1 + \alpha_3^{bilateral'''} x_3 + c^{bilateral'''}$$

  and obtain

$$\frac{\beta_1}{\nu\zeta(\rho+\phi)} = \hat{\alpha}_1^{bilateral'''}, \quad -\frac{2}{\nu\zeta}\bar{\kappa} = \hat{c}^{bilateral'''}$$

We then estimate ϕ and $\nu\zeta$ similarly as above, after setting:

$$network\_TFP = -\frac{\beta_1(l_t^{n,jn} - l_{t-1}^{n,jn})}{(\rho+\phi)\nu\zeta}\log B^{rn} + \frac{\rho\beta_1 l_t^{n,jn}}{(\rho+\phi)\nu\zeta}\log B^{rn} = \hat{\alpha}_1^{bilateral}(l_t^{n,jn} - l_{t-1}^{n,jn})\log B^{rn} + \rho\hat{\alpha}_1^{bilateral} l_t^{n,jn}\log B^{rn}$$

$$network\_cost = -\frac{\rho}{\nu\zeta}\bar{\kappa}$$

Steps for Recovering $\bar{\kappa}^{n,k}, \alpha_0, \beta_0$ With the estimates of parameters related to job-switching and the firm-level coworker influences in hand, we turn to estimating the baseline sector-level adjustment costs, $\bar{\kappa}^{n,k}$, for each sector pair, as well as the parameters characterizing the sector-level coworker network, α_0 and β_0. Since the cross-sector flows now depend on the inclusive values of being employed in any firm in a sector, which do not take on any simple analytical forms that could be directly mapped to observables in the data, we resort to model simulation at the steady state using the following steps. First, we rewrite the cross-sector flows as:

$$\begin{aligned} &\zeta(S_t^{jn,k} - S_t^{ik,k}) - \zeta(S_t^{jn,n} - S_t^{ik,n}) = \\ &\log\frac{\mu_t^{jn,k}}{\mu_t^{jn,n}} + \log\frac{\mu_t^{ik,n}}{\mu_t^{ik,k}} - \frac{\beta_0}{\nu(\rho+\phi)}\left[(l_t^{k,jn} - l_t^{k,ik})\log(Z_t^k) - (l_t^{n,jn} - l_t^{n,ik})\log(Z_t^n)\right] - \frac{\alpha_0}{\nu}\left[l_t^{k,jn} + l_t^{n,ik}\right]\bar{\kappa}^{n,k} \end{aligned} \tag{E.12}$$

- Take the flow variables $\mu_t^{jn,k}, \mu_t^{jn,n}, \mu_t^{ik,n}, \mu_t^{ik,k}, l_t^{k.jn}, l_t^{k,ik}, l_t^{n,jn}, l_t^{n,ik}$ from the data at the steady state. For a given set of $\theta = \{\alpha_0, \beta_0, \kappa^{n,k}\}_{n,k\in\mathcal{N}}$, we can calculate the data-implied inclusive values $S_{data}^{jn,k}(\theta,\mu), S_{data}^{ik,k}(\theta,\mu)$, $S_{data}^{jn,n}(\theta,\mu), S_{data}^{ik,n}(\theta,\mu)$ at the steady state.
- Since all other parameter values are known at this point, we can calculate the model-implied inclusive values $S_{model}^{jn,k}(\theta), S_{model}^{ik,k}(\theta), S_{model}^{jn,n}(\theta), S_{model}^{ik,n}(\theta)$ using the steps detailed in Appendix E.1 at the steady state. Denote:

$$S_{model}^{jn,ik} = S_{model}^{jn,k} - S_{model}^{ik,k} - S_{model}^{jn,n} + S_{model}^{ik,n}$$
$$S_{data}^{jn,ik} = S_{data}^{jn,k} - S_{data}^{ik,k} - S_{data}^{jn,n} + S_{data}^{ik,n}$$

  where we omit the dependence on θ and the data μ, l_- for simplicity of notation.
- Our moment condition is:

$$\mathbb{E}[\zeta(S_{model} - S_{data})] = 0$$

  where S is the vector that stacks all $S^{jn,ik}$ for $n \neq k$.
- We first minimize the objective function:

$$Q(\theta) = (S_{model} - S_{data})'(S_{model} - S_{data})$$

  and obtain $\hat{\theta}_1$.
- We then obtain the optimal weighting matrix $\hat{C}^{-1}$ where:

$$\hat{C} = \frac{1}{n}\sum(S_{model} - S_{data})(S_{model} - S_{data})'$$

and minimize the objective function:

$$Q'(\theta) = (S_{model} - S_{dataC})'\hat{C}(S_{model} - S_{data})$$

and obtain our estimates $\hat{\theta}$.

E.5 Additional Tables from Estimation

Table E1: Estimated Values for Sector- and Firm-level Productivity

Sectors	$\log(\tilde{Z})$	δ	Firm AKM FE Quartile	$\log(B)$
Agriculture and Mining	3.10	0.08	1	-0.59
			2	-0.08
			3	-0.02
			4	0.83
Manufacturing	4.23	0.03	1	-1.20
			2	-0.29
			3	0.29
			4	1.20
Utilities, Water Supply, Waste Management	3.19	0.04	1	-1.37
			2	-0.32
			3	0.48
			4	1.25
Construction	3.72	0.03	1	-1.13
			2	-0.03
			3	0.44
			4	0.85
Trade, Transportation, and Storage	4.26	0.04	1	-0.97
			2	-0.16
			3	0.45
			4	0.68
Information and Professional Services	4.06	0.08	1	-1.00
			2	0.00
			3	0.32
			4	1.10
Financial, Insurance, and Real Estate	3.40	0.04	1	- 1.26
			2	-0.56
			3	0.15
			4	1.50
Accommodation, Administration, Arts, Other Services	4.33	0.04	1	-0.75
			2	-0.14
			3	0.43
			4	0.58
Education and Health Services	4.26	0.04	1	-0.90
			2	0.00
			3	0.35
			4	0.70

Note: Table shows the estimated values for logged sector- and firm-level productivity.

Table E2: Wage by Sector

Sectors	Wage (Mean)
Agriculture and Mining	28.16
Manufacturing	30.41
Utilities, Water Supply, and Waste Management	31.93
Construction	28.58
Trade, Transportation, and Storage	27.18
Information and Professional Services	34.36
Financial, Insurance, and Real Estate	31.92
Accommodation, Administration, Arts, Other Services	26.17
Education and Health Services	27.84

Note: Table shows the mean wages by sector averaged across all years.

Table E3: Gross Flows across Sectors

	Agri/Min	Manuf	Util	Const	Trade/ Trans	IT/ Prof Serv	Fin/Re	Accom/ Admin	Educ/ Health
Agri/Min	0.845	0.020	0.003	0.016	0.036	0.019	0.002	0.049	0.010
Manuf	0.001	0.895	0.001	0.010	0.031	0.012	0.002	0.039	0.008
Util	0.002	0.015	0.876	0.015	0.033	0.010	0.002	0.041	0.006
Const	0.003	0.028	0.004	0.849	0.034	0.011	0.005	0.060	0.007
Trade/ Trans	0.002	0.026	0.002	0.010	0.880	0.014	0.003	0.052	0.011
IT/ Prof Serv	0.010	0.024	0.002	0.009	0.030	0.865	0.008	0.049	0.014
Fin/ Re	0.001	0.010	0.001	0.010	0.019	0.024	0.894	0.035	0.009
Accom/ Admin	0.002	0.034	0.003	0.016	0.049	0.019	0.005	0.846	0.027
Educ/ Health	0.001	0.010	0.001	0.003	0.013	0.010	0.002	0.041	0.922

Note: Table shows the flows across sectors. Origin sector is listed by row, and destination sector is listed by column.

Table E4: Job Switching Elasticity, Switching Rate, and Firm-level Coworker Network

	(1)	(2)	(3)	(4)
Panel (A): Regression Estimates of Equation (38)				
Relative Wage, $\log \frac{w^{rn}}{w^{jn}}$	1.924^{***}	1.947^{***}	1.886^{***}	1.975^{***}
	(0.1601)	(0.0232)	(0.0249)	(0.0232)
Panel (B): Regression Estimates of Equation (37)				
$l_t^{n,jn} \log B^{rn} - l_t^{n,jn} \log B^{jn}$	0.954^{***}			0.964^{***}
	(0.1726)			(0.1902)
$l_t^{rn,jn} + l_t^{jn,rn}$	52.86^{***}		52.71^{***}	
	(10.2880)		(8.9756)	
Panel (C): Implied Parameter Values				
Job-Switching Elasticity, $\frac{1}{\nu}$	0.38	0.39	0.38	0.40
Influence on Moving Costs, α_1	7.05	0	7.03	0
Influence on TFP Perception, β_1	1.16	0	0	1.15
Coworker Influence on perceived TFP, $\beta_1 \neq 0$		✓	✓	
Coworker Influence on adjustment cost, $\alpha_1 \neq 0$		✓		✓

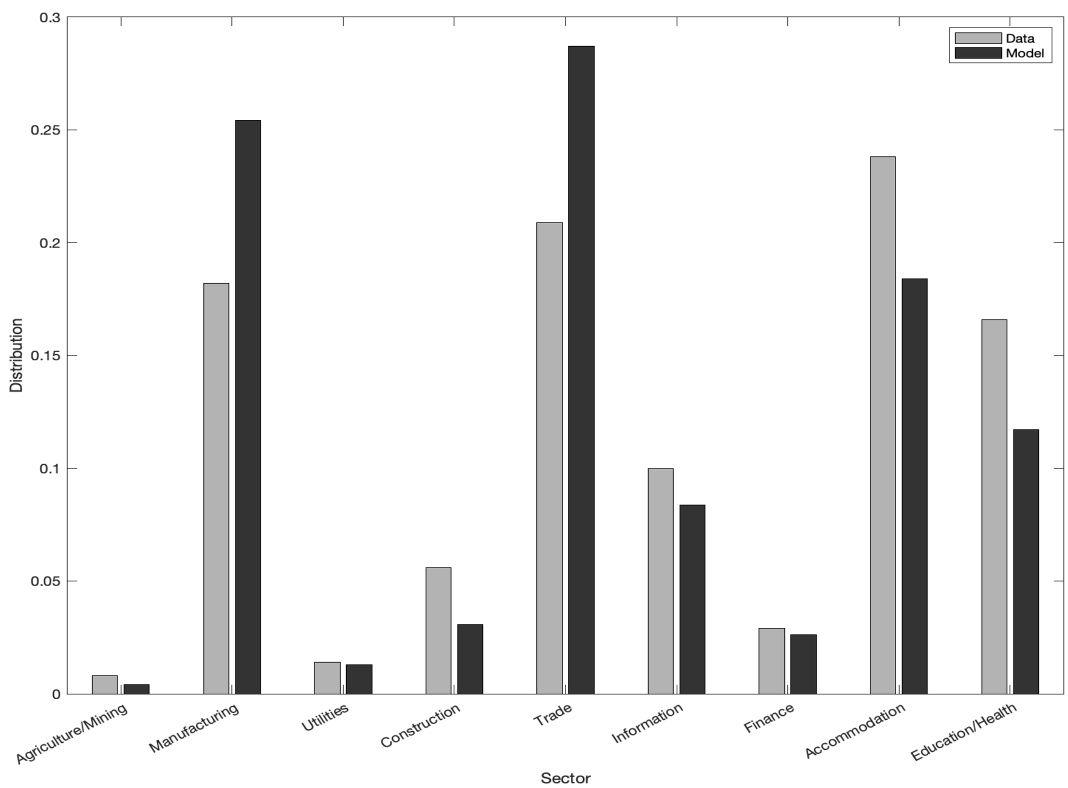
Notes: Table displays the coefficient estimates obtained from equation (36) and (37), where we set $\rho = 0.05$, $\phi = 2.3$, $\zeta = 0.2$, and $\bar{\kappa} = 15$. Standard errors are clustered at the origin establishment level. Column (1) assumes that coworker network can influence both the TFP perception and the adjustment cost across firms that are within the same sector, so that $\alpha_1 \neq 0$ and $\beta_1 \neq 0$. Column (2) assumes that coworker network has no inherent influence on sectoral choice, so $\alpha_1 = 0$ and $\beta_1 = 0$. Column (3) assumes that coworker network can only influence the cost for switching, so $\alpha_1 \neq 0$ and $\beta_1 = 0$. Column (4) assumes that coworker network can only influence the perceived TFP, so $\beta_1 \neq 0$ and $\alpha_1 = 0$. Panel (B) backs out the implied parameters values from the coefficient estimates in panel (A). Panel (A) displays the estimates for equation (36) and panel (B) displays the estimates for equation (37). Panel (C) shows the parameter values backed out from the two regressions.

Table E5: Sector-Level Transition Costs

	Agri/Min	Manuf	Util	Const	Trade/ Trans	IT/ Prof Serv	Fin/Re	Accom/ Admin	Educ/ Health
Agri/Min	0	6.24	4.63	5.37	6.83	4.25	1.28	6.90	3.15
Manuf	6.24	0	6.04	8.91	11.32	8.96	5.33	11.59	7.23
Util	4.63	6.04	0	6.61	7.75	4.87	1.96	7.46	2.59
Const	5.37	8.91	6.61	0	9.51	7.58	6.51	10.33	4.77
Trade/ Trans	6.83	11.32	7.75	9.51	0	10.24	7.12	12.36	8.79
IT/ Prof Serv	4.25	8.96	4.87	7.58	10.24	0	8.18	11.56	8.92
Fin/ Re	1.28	5.33	1.96	6.51	7.12	8.18	0	8.63	5.42
Accom/ Admin	6.90	11.59	7.46	10.33	12.36	11.56	8.63	0	11.06
Educ/ Health	3.15	7.23	2.59	4.77	8.79	8.92	5.42	11.06	0

Note: Table shows the estimated baseline transition costs across sectors. Origin sector is listed by row, and destination sector is listed by column. We assume that own-sector transition cost is zero and the transition costs are symmetric across origin and destination sector pairs, so $\bar{\kappa}^{n,k} = \bar{\kappa}^{k,n}, \forall k, n \in \mathcal{N}$.

Figure E1: Labor Distribution by Sectors



Note: Figure shows the labor share by sector in the data and according to the model, both at the steady state.

Table E6: Labor Distribution by Firms

Sectors	Firm AKM FE Quartile	Labor Share (Data)	Labor Share (Model)
Agriculture and Mining	1	0.001	0.001
	2	0.002	0.001
	3	0.002	0.001
	4	0.003	0.002
Manufacturing	1	0.004	0.017
	2	0.020	0.038
	3	0.039	0.062
	4	0.119	0.138
Utilities, Water Supply, Waste Management	1	0.000	0.001
	2	0.001	0.002
	3	0.003	0.003
	4	0.010	0.007
Construction	1	0.004	0.002
	2	0.010	0.007
	3	0.020	0.010
	4	0.022	0.013
Trade, Transportation, and Storage	1	0.017	0.027
	2	0.042	0.054
	3	0.076	0.093
	4	0.074	0.113
Information and Professional Services	1	0.004	0.006
	2	0.010	0.016
	3	0.023	0.021
	4	0.063	0.041
Financial, Insurance, and Real Estate	1	0.001	0.002
	2	0.002	0.003
	3	0.004	0.005
	4	0.022	0.017
Accommodation, Administration, Arts, Other Services	1	0.040	0.021
	2	0.082	0.036
	3	0.055	0.059
	4	0.061	0.068
Education and Health Services	1	0.011	0.011
	2	0.036	0.025
	3	0.052	0.034
	4	0.067	0.046

Note: Table shows the labor share by firm in the data and according to the model, both at the steady state.

Table E7: Model vs. Data Sector-Level Transition Matrix at Steady State

	Agri/Min	Manuf	Util	Const	Trade/ Trans	IT/ Prof Serv	Fin/Re	Accom/ Admin	Educ/ Health
1	-0.1234	0.0224	0.0007	0.0096	0.0336	0.0041	-0.0051	0.0535	0.0046
2	-0.1344	0.0202	0.0053	0.0117	0.0419	0.0028	-0.0048	0.0529	0.0045
3	-0.1217	0.0158	0.0037	0.0109	0.0482	0.0025	-0.0042	0.0435	0.0012
4	-0.1038	0.0155	0.0024	0.0075	0.0151	0.0508	-0.0044	0.0179	-0.0009
5	0.0026	-0.1535	0.0015	0.0111	0.0533	0.0080	0.0016	0.0583	0.0171
6	0.0020	-0.1342	0.0015	0.0102	0.0428	0.0063	0.0013	0.0591	0.0109
7	0.0012	-0.1005	0.0015	0.0084	0.0339	0.0091	0.0011	0.0390	0.0062
8	0.0003	-0.0461	0.0006	0.0031	0.0125	0.0110	0.0008	0.0157	0.0020
9	0.0105	0.0292	-0.2268	0.0507	0.0658	0.0025	-0.0017	0.0682	0.0015
10	0.0054	0.0142	-0.1462	0.0171	0.0567	0.0050	-0.0021	0.0465	0.0034
11	0.0019	0.0175	-0.1270	0.0153	0.0484	0.0055	-0.0001	0.0374	0.0012
12	0.0005	0.0068	-0.0506	0.0054	0.0134	0.0095	-0.0007	0.0160	-0.0003
13	0.0011	0.0142	0.0013	-0.1231	0.0295	0.0071	0.0030	0.0632	0.0036
14	0.0016	0.0190	0.0031	-0.1175	0.0273	0.0065	0.0040	0.0518	0.0043
15	0.0019	0.0186	0.0031	-0.1062	0.0240	0.0080	0.0035	0.0431	0.0040
16	0.0014	0.0181	0.0032	-0.0859	0.0188	0.0104	0.0028	0.0288	0.0023
17	0.0019	0.0170	0.0020	0.0096	-0.1156	0.0076	0.0021	0.0625	0.0129
18	0.0020	0.0209	0.0029	0.0079	-0.1126	0.0095	0.0018	0.0570	0.0105
19	0.0014	0.0196	0.0024	0.0070	-0.0912	0.0104	0.0018	0.0413	0.0074
20	0.0007	0.0162	0.0015	0.0040	-0.0693	0.0135	0.0017	0.0260	0.0056
21	0.0010	0.0142	0.0011	0.0084	0.0384	-0.1644	0.0052	0.0799	0.0162
22	0.0008	0.0150	0.0014	0.0056	0.0270	-0.1163	0.0056	0.0429	0.0181
24	0.0001	0.0189	0.0012	0.0029	0.0201	-0.0927	0.0108	0.0298	0.0089
25	-0.0009	0.0079	0.0003	0.0179	0.0321	0.0163	-0.1518	0.0637	0.0144
26	0.0004	0.0086	0.0006	0.0195	0.0257	0.0214	-0.1631	0.0720	0.0148
27	-0.0001	0.0073	-0.0002	0.0114	0.0257	0.0203	-0.1254	0.0526	0.0084
28	-0.0006	0.0035	-0.0003	0.0024	0.0068	0.0173	-0.0480	0.0160	0.0029
29	0.0019	0.0352	0.0025	0.0132	0.0605	0.0148	0.0028	-0.1507	0.0198
30	0.0014	0.0521	0.0026	0.0132	0.0602	0.0159	0.0037	-0.1691	0.0201
31	0.0009	0.0222	0.0018	0.0080	0.0337	0.0211	0.0040	-0.1141	0.0223
32	0.0005	0.0125	0.0016	0.0034	0.0131	0.0160	0.0024	-0.0679	0.0184
33	0.0004	0.0046	-0.0001	0.0015	0.0110	0.0053	0.0010	0.0295	-0.0531
34	0.0003	0.0046	-0.0001	0.0015	0.0105	0.0054	0.0010	0.0337	-0.0570
35	0.0001	0.0033	-0.0001	0.0009	0.0084	0.0068	0.0011	0.0300	-0.0504
36	0.0000	0.0027	-0.0001	0.0003	0.0038	0.0088	0.0006	0.0193	-0.0355

Note: Tale shows the difference between the sector-level transition matrix in the data and the sector-level transition matrix estimated at the steady state. Origin firm is listed by row, and destination sector is listed by column. The firm groups are numbered such that each four firms belong to the same sector, with a smaller number corresponding to a lower AKM firm FE quartile. We assume that own-sector transition cost is zero and the transition costs are symmetric across origin and destination sector pairs, so $\bar{\kappa}^{n,k} = \bar{\kappa}^{k,n}, \forall k, n \in \mathcal{N}$.

Table E8: Estimated Productivity Shock by Sector

Sectors	Shock
Agriculture and Mining	4.1%
Manufacturing	-0.9%
Utilities, Water Supply, and Waste Management	3.8%
Construction	0.8%
Trade, Transportation, and Storage	-0.8%
Information and Professional Services	2.1%
Financial, Insurance, and Real Estate	-0.7%
Accommodation, Administration, Arts, Other Services	-4.8%
Education and Health Services	-4.2%
All Private Sectors	-0.3%

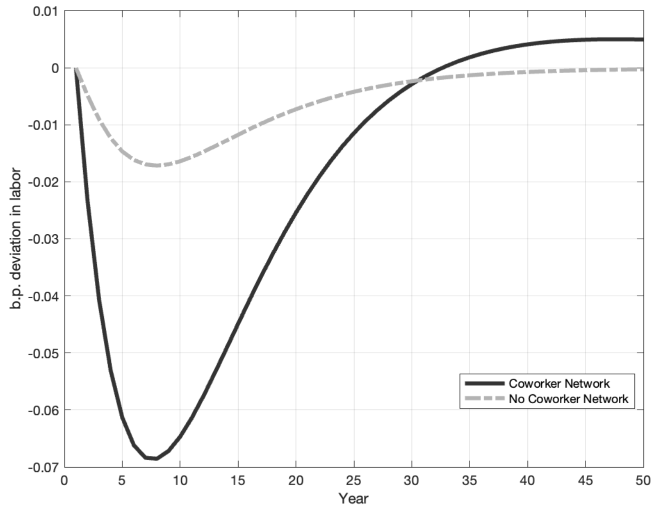
Note: Table shows estimated productivity shock by sector brought about by COVID.

F Additional Quantitative Results

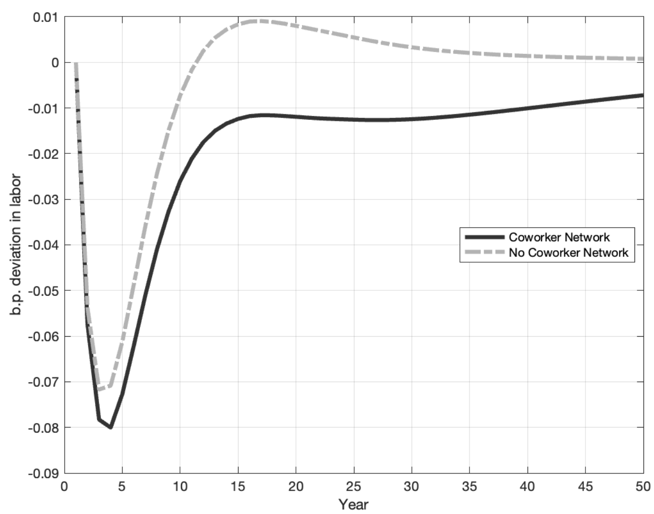
F.1 Illustrative Plots

Figure F1: Labor Responses to a Negative Shock

(A) Shock to Construction

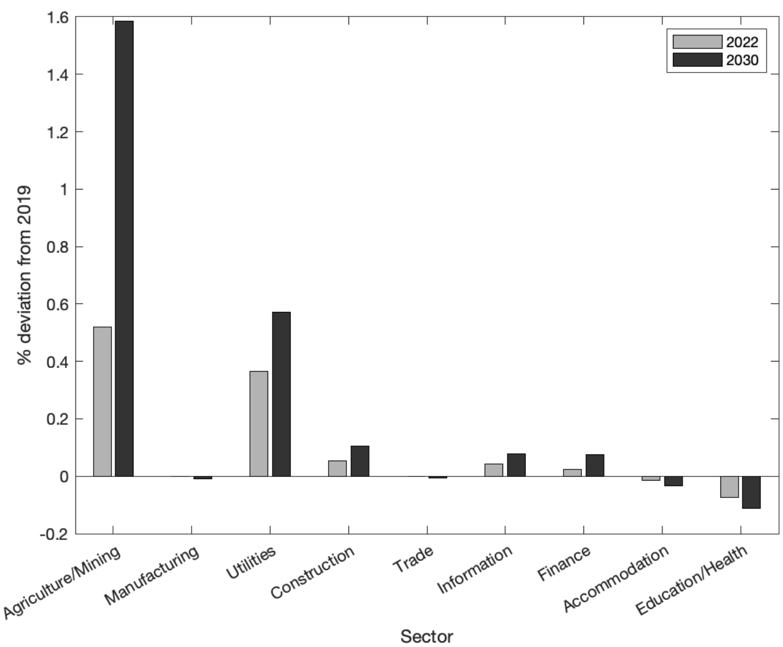


(B) Shock to Education and Health Services



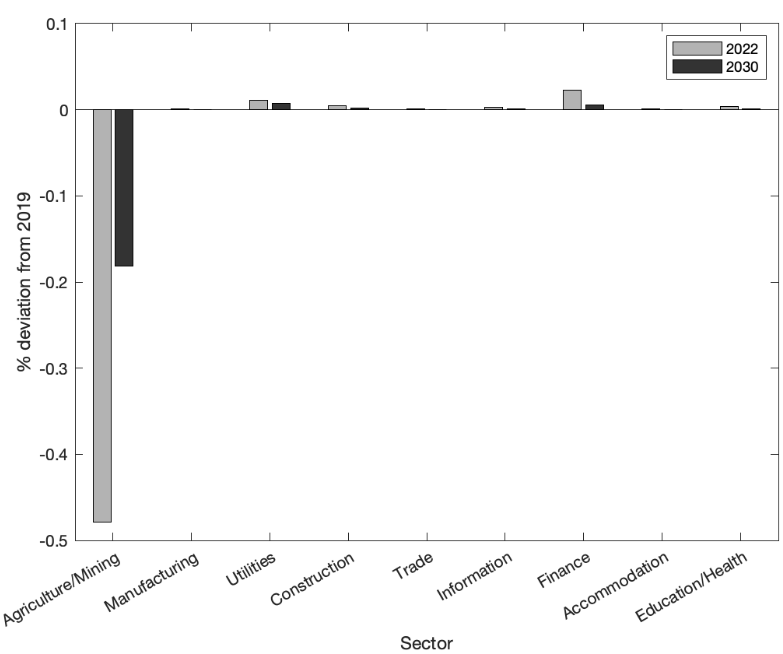
Note: Figure plots own-sector labor responses to a 10% negative productivity shock, assuming that other sectors have no loading on the shock. Panel (A) plots the labor deviation from steady state when the shock happens to the construction sector, and Panel (B) assumes that the shock happens to the education and health services sector. The solid black line represents the implied responses from our model with coworker network. The dashed gray line represents the implied responses in a model with no influence from coworker network and agents are know perfectly the TFP in each firm and industry.

Figure F2: Labor Distribution by Sectors (% deviation from s.s.)



Note: Figure shows the predicted percentage deviation in labor distribution by sector in 2022 and 2030, compared to the pre-COVID level in 2019, under the baseline model.

Figure F3: Labor Distribution by Sectors (% deviation from s.s.; no coworker network)



Note: Figure shows the predicted percentage deviation in labor distribution by sector in 2022 and 2030, compared to the pre-COVID level in 2019, under the model where all coworker-related parameters are set to 0.