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Essays on Innovation, Productivity and Labor Economics

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Essays on Innovation, Productivity and Labor Economics

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Contents

Introduction

In the following thesis I study how innovation affects labor markets: how it originates and what are its consequences for the labor force. In the first two chapters the source of an increase in productivity and innovative activity are co-worker networks. I explore their role in boosting firms' performance and facilitating knowledge transmission. The third chapter focuses on automation, which itself is a product of an increase in innovative activity. In that chapter I study how automation affects employment structure, with particular emphasis on displaced workers: their occupational choices and human capital.

In Chapter 1 of this thesis, *To work or to network? - a study of firm hiring decisions*, I investigate the effect of social network on firm performance. It is estimated that between 30% and 60% of all jobs are obtained through social connections with around 71% of firms having introduced a formal referral program. Workers benefit from social connections (e.g. Cingano and Rosolia (2012), Dustmann et al. (2016)), however, the motives behind employers' reliance on informal links remain largely unexplored. What renders informal contacts attractive to employers? Does firm's social network simply speed up the hiring process or it additionally facilitates selection of high-skilled individuals?

Using matched employer-employee data from Veneto, an industrial region in northern Italy, this chapter studies the role of co-worker links in firms' hiring decisions and its consequences for productivity and output. Novel empirical findings show that the hires from firm's own co-worker network increase significantly its productivity. I conclude that 10% surge in connected hires increases productivity by approximately 1%. The event study analysis reveals that the effect lasts up to three years following the hire. The evidence points that the co-worker links increase firm productivity mainly through industry-specific skills, which suggests that employers may use informal contacts to poach high-skilled workers. I also show that informal ties play a larger role in job transitions within industrial clusters. Hence, social networks might facilitate the transmission of job-specific skills and knowledge diffusion.

In Chapter 2, *Inventors' Coworker Networks and Innovation* (joint with Sabrina Di Addario and Michel Serafinelli), we build on the previous chapter by studying the role of coworker network in plants' innovative activity and knowledge diffusion. We focus on the patenting activity of inventors and their coworker networks. This chapter presents direct evidence showing the extent to which plants' innovation is affected by access to knowledgeable labor connected through the co-worker network.

We use a unique dataset that matches administrative employer-employee records from north-central Italy, a region with many successful industry clusters, to patent data for the period 1987-2008. Displacements of inventors due to plant closures generate labor supply shocks to plants that employ their previous co-workers. We estimate (a) event-study models where the treatment is the displacement of a connected inventor and (b) IV specifications where we use the displacement of a connected inventor as instrument for the hire of a connected inventor. Estimates indicate that the improved capacity to employ inventors within their employees' network increases plants' patenting activity. We also present the evidence that the additional output is a combination of patents authored by the newly hired connected inventors (either solo-authored or with co-authors outside the receiving plant) and patents resulting from a collaboration among the hired connected inventors and other workers within the receiving plants. Interestingly, we also observe an increase in patents authored by the other workers within the new plants (without the hired connected inventors), a sign of either peer pressure or knowledge transfer.

In Chapter 3, *Job Automation and Worker Reallocation*, I study the effects of job automation on labor markets and displaced workers. Several works document labor-displacing nature of job automation (e.g. Acemoglu and Restrepo (2017a), Bessen et al. (2019)), however, we know surprisingly little about its consequences for the employment distribution. How does job automation affect reallocation decisions of displaced workers?

I show that stagnant occupational mobility rates reported since 1990s are the result of a composition effect: positive trend for occupations with high risk of automation is offset by the decline in mobility among low risk occupations. Displaced workers with high exposure to automation have on average 10 percentage points higher probability of changing their broad occupational category, a pattern that has increased significantly over the past two decades. The mobility rates within high exposure occupations are monotone, pointing that low earners switch their occupations more frequently. Furthermore, the direction of mobility is downward: individuals at risk of automation switch into occupations with lower average wages.

To evaluate the role of job automation in the evolution of occupational mobility, this chapter proposes a search and matching model with technological acceleration and human capital accumulation. The reallocation decision of unemployed individuals depends on their human capital level and skill transferability between two occupations. The results show that the response of the economy to automation shock follows closely patterns observed in the data between 1996 and 2012. Job automation accounts for 79 percent of the increase in mobility gap. This in turn leads to output losses due to skill transferability mechanism and the fact that human capital is not fully transferable across occupations. Policy counterfactuals indicate that off-the-job training for workers at risk of automation can reduce the output loss by nearly 20 percent.

Chapter 1

To work or to network? - a study of firm hiring decisions

1.1 Introduction

The percentage of jobs obtained through referrals varies between 30 and 60%, depending on the country and profession.[1] The popularity of employee referral programs rises, as novel techniques of referral recruitment are being introduced. It is estimated that around 71% of private companies, typically large employers, have a formal referral program.[2] Firms that already implemented employee referral programs claim that its main objective is to 'Increase Quality' (93% point that answer), novel recruitment techniques include a third party referral tools and beyond 'employees' referral programs.[3] The literature documents that referred workers, compared with those who applied without any referral, are not only more likely to be hired, but also enjoy an initial wage premium.[4] The consequences of using informal links for employers and the motives behind reliance on social network remain, however, largely unexplored. Existing literature attributes the use of

[1] Montgomery (1991) presents a summary of the labor surveys collected by Myers and Schultz (1951), Rees and Schultz (1970), *Granovetter* (1974) or *Corcoran* (1981), where the percentage of jobs found using friends and relatives is documented for various occupational and demographic groups. The largest survey by *Corcoran* (1981) finds that around 52% of White males got their job through referrals, compared to 47% of White females, 58% of Black males and 43% of Black females.

[2] Meritage Talent Solutions conducted a survey of 100 recruiting organizations and reports the trends in employee referral programs. They document that 86% of firms with more than 50,000 employees have formal referral programs, whereas only 59% of companies with fewer than 500 workers claim to use those. Higher popularity of referral programs for large firms may be surprising, intuitively we associate referrals with small or medium firms, however one has to remember about the prevalence of strong ties within those structures.

[3] Remaining options are 'Increase Quantity' (61%), 'Decrease Time to Hire' (58%), 'Increase Retention' (49%), 'Increase Diversity' (32%) or 'Other' (9%). In 2014 around 14% of firms participating in employee referral programs used third party referral tools, whereas 27% of firms planning to launch a program considered to do so with third party tools. Those are typically companies that scan workers social network and provide the recruiting firm the best match based on the available information. Beyond employee programs are based on ties provided by alumni, customers, social media connections, etc.

[4] See e.g. Dustmann et al. (2016), Brown et al. (2016) or Cappellari and Tatsiramos (2015)

informal contacts to information frictions at the hiring stage.[5]

The main goal of this paper is to measure the impact of socially connected hires on firm performance and revisit the existing hypotheses on why do firms rely on their social network at the hiring stage.[6] To the best of my knowledge this work is the first to examine the impact of connected hires on firm productivity using the structural approach to production function estimation and detailed administrative records. The strategy of distinguishing socially connected hires follows the co-worker network approach proposed by Hensvik and Skans (2016). I first distinguish socially connected hires using former co-worker links in the matched employer-employee dataset from Veneto, the industrial region in northern Italy. Then, I measure the effect of connected hires on firm productivity and output, employing labor supply shocks generated by mass-layoffs. The remaining part of the analysis explores the geographical dimension of socially connected hires within industrial clusters and transmission of industry-specific skills.

The existing empirical literature (e.g. Hensvik and Skans (2016)) identifies socially connected hires in the large administrative datasets with the use of co-worker links. I build on this literature by i) constructing matched employer-employee panel of firms that hire through co-worker links and ii) measuring their performance given the detailed balance sheet data. The matched employer-employee dataset is constructed using Veneto Workers Histories (hereafter VWH) and Bureau van Dijk AIDA datasets. New hires are denoted as socially connected (or more precisely: linked) if they share work history with at least one of the incumbent workers. The share of connected hires in the Veneto dataset matches findings of previous studies (11.2 percent of all hires, opposed to 12 percent in Hensvik and Skans (2016)). The estimates of hiring probability, initial wage premium and job tenure of connected hires follow closely previous findings. Controlling for job-to-job transition and the same industry link reveals that in fact, the effect of co-worker links is largely driven by transmission of job- or industry-specific skills.

The core analysis employs time-varying, structural productivity estimation framework introduced by Olley and Pakes (1996). The estimates reveal significant and positive impact of linked hires on firm productivity and output that can last up to 3 years following the hire. The increase of linked hires by 10% increases firm productivity by approximately 1%. Interestingly, surge in productivity happens mainly due to linked, same industry hires, suggesting the role of co-worker links in the transmission of job-specific skills. Similar results are found for the firm output. To address the issue of potential endogeneity of firm hiring decisions I construct instrumental variable based on firm's co-worker network and mass displacements of workers. The former is defined as all former co-workers of incumbent employees within past five years, whereas displacements were

[5]For the detailed description of existing empirical evidence and micro theories on the usage of social connections by firms look at Section 1.2.

[6]Detailed description of existing theories of firms' motives behing the use of social connections is provided by Section 1.2

part of the mass-layoffs in industry different than the firm of interest. In other words, instrumental variable captures the exogenous labor supply shock among workers connected to the firm. The results of instrumental variable confirm the baseline findings.

Finally, following the findings on the importance of same-industry connected hires, I explore the geographical dimension with the use of industrial districts, a clusters of firms with particular economic specialization in distinctive geographical areas. I document higher frequency of connected hires within industrial districts. Linked hires within industrial clusters experience 5.4% wage premium, compared with 3% of non-linked ones.[7] The study of worker flows suggests that firms attract employees via informal channels from high productivity firms. The findings is in line with the adverse selection hypothesis of firms poaching skilled employees thanks to social connections. It elicits potential role of co-worker links in transmission of job-specific skills and facilitation of knowledge diffusion.

The main contribution of this paper is documenting the differences in productivity that stem from firms' reliance on social network and emphasising the role of co-worker links in transmission of job-specific skills. Another contribution of the work is the distinction of heterogeneity within connected hires, highlighting the relevance of social network in job transitions within specialized industrial districts, so far absent in the literature.

The paper proceeds with the brief review of the existing literature and hypotheses on firms' reliance on referrals in Section 1.2. Methodology and empirical strategy are described in Section 1.3, followed by information on the data, merger and summary statistics in Section 1.4. The results, robustness checks and extensions are provided by Section 1.5. Section 1.6 concludes, whereas all additional statistics, results and placebo checks are reported in the Appendix A.

1.2 Related Literature and Theoretical Background

The existing literature on referrals is dominated by theoretical papers. In their seminal works Calvó-Armengol and Jackson (2004, 2007) study the spread of information in the network and its consequences. The main finding of Calvó-Armengol and Jackson (2004) states that in the unique steady-state, employment statuses of any path-connected agents are positively correlated across time. One of the first attempts to incorporate the weak ties into formal matching model was pursued by Calvó-Armengol and Zenou (2005), where agents were allowed to search for a job through official and informal channels. The network size was a key object in this framework, providing advantage in job finding probability. Galenianos (2014) investigates the social planner's problem for a matching model with information transmission and finds that the equilibrium is inefficient in terms of matching accuracy. In his earlier work, Galenianos (2013) considers firm heterogeneity

[7] The reference group are non-linked outside industrial cluster hires.

and shows that smaller firms rely more on the informal channels of information spread, a finding that gained some empirical support.[8]

The empirical literature uses firm level data, labor force surveys or the administrative records in order to quantify the effect of referrals on individual job performance. Stylized facts document the advantage of referred workers in hiring probability, initial wage premium and longer job tenure (e.g. Dustmann et al. (2016), Brown et al. (2016), Glitz and Vejlin (2019)). Higher cognitive skills of referred employees were reported by Hensvik and Skans (2016), with the use of armed-force test. Several works show significant, positive correlation between network employment rate and the probability of finding a job (e.g. Cingano and Rosolia (2012), Saygin et al. (2014), Glitz (2017)).[9] Referral recipients are not the only ones who benefit from the match, Heath (2018) claims that the wages of the recipient-provider pairs are positively correlated over tenure. Rebien et al. (2017) document that small and medium firms use referrals to higher extent.

The firm side of referral usage is yet absent in the literature, with few exceptions that focus on solely on firm hiring decisions. There are two main hypotheses on why do firms use referrals: adverse selection and moral hazard problem. The former comprises a wide range of theories that assume that the whole problem boils down to signalling game between employer and job candidate. Referrals provide more accurate signal on candidate abilities, since employers (apart from the interview) have a valuable insight from a referee. Theoretical search framework with referral signal accuracy was first introduced by Simon and Warner (1992), later developed by e.g. Galenianos (2014), Dustmann et al. (2016) and Glitz and Vejlin (2019). Glitz and Vejlin (2019) structurally estimate the model and find that the noise of the signal about worker's ability is 14.5 percent lower for referred hires than for the non-referred ones. Firms are absent in the aforementioned models, they could potentially benefit from referrals by saving vacancy costs (as suggested by Eliason et al. (2018a)).[10] Montgomery (1991) goes even further and claims that firms not only use referrals to omit signalling problem but also to poach high skilled workers. Following this argument, firms should experience surge in productivity, since referrals provide better skilled workers than formal markets.

The moral hazard hypothesis was originated by Heath (2018) and focuses on pairs of workers established by referral - its recipient and provider. By creating such pairs employers may exert higher effort from the recipients. The presence of the provider at the workplace may additionally induce the recipient to perform better and as a result wages of the pair may be positively correlated. Referred workers tend to be in this framework of

[8]Rebien et al. (2017) investigate the referrals from firms' perspective and find the negative correlation between firm size and the use of weak ties. For other matching or dyad models with social network see e.g. Fontaine (2003, 2008), Zaharieva (2013, 2015), Zenou (2015).

[9]Social network is there defined as all former co-workers of the unemployed within last 5 years. Unemployment spell is preceded by firm closure.

[10]Their model, however, does not explicitly assume adverse selection problem on the firm side. Relying on social network is just a form of saving the costs, without any heterogeneity of workers.

lower quality, however, higher effort exerted by them may improve firm output. On the other hand, in case of low output, firms can punish both provider and recipient, hence the overall effect remains ambiguous. Heath (2018) tests model predictions using a household survey of the workers of garment factories in Bangladesh.[11]

Most closely related with this paper is the recent work by Eliason et al. (2018a), who use Swedish administrative records to uncover how the displacement shocks affect firms' hiring decisions and social connections. The impact on firm productivity is not their primary focus, it is measured using revenue per worker. The following work differs with that respect as it proposes structural productivity estimation using detailed firm balance sheet data. It also explores the dynamics of the effect of connected hires on firm productivity using event study framework. The findings of this work lean towards the adverse selection hypothesis of firms poaching high skilled workers with the use of referrals. Thanks to co-worker links firms experience the surge in productivity, there is also a suggestive evidence of employers poaching new hires from higher-productivity companies. Modelling hiring decisions and outcomes as well as the analysis of potential role of social network in knowledge diffusion are one of the main challenges in the literature.

1.3 Methodology

1.3.1 Referral Identification

Following the approach proposed by Hensvik and Skans (2016) (hereafter HS), this paper distinguishes referred hires with the use of co-worker links. More precisely, if a new hire shares working history with any of the incumbents within last 5 years, I denote her as a connected hire. The idea of co-worker links relates to the classical approach of Montgomery (1991), who argued that the process of hiring through referral consists of two stages: first, newly hired workers reveal their type, and second, employers ask the high types to refer new workers from their social network. Observed inbreeding of social network increases the probability of hiring worker of a high type through referrals.

Given the matched data from Veneto region, the co-worker links are distinguished in the same manner as in HS, with the precision to weeks. Incumbents are defined as those who entered the establishment at least 3 weeks before a new hire, whereas the latter need necessarily to enter the firm for the first time in their career. Only firms with less than 500 workers are taken into account. Employees in large establishments may not have a

[11]The empirical analysis is performed in low-skill occupations, what may rise some concerns. The additional analysis of entrant-incumbent pairs conveyed for the purpose of this work reveals similar patterns of substantial inbreeding of provider-recipient pairs as well as significant, positive correlation of their wages over tenure. It proves the existence of moral hazard not only within low-skilled workers. The additional results are not included in the Appendix, since they are not the main focus of the paper. Provider-recipient pair analysis is available upon request.

chance to establish a link, social networks do not always overlap. The employment spells of incumbents and hires in the past establishment have to be longer than 3 weeks and need to overlap by at least one week. Other possible challenge for the measure posed by the administrative data are firm mergers. To address this issue, entrants who arrive from the same firm in groups of more than 5 are excluded.

1.3.2 Empirical Strategy

Referral Heterogeneity

In the first part of the analysis I study heterogeneity of connected hires and its impact on job performance. The source of heterogeneity is the length of unemployment spell before the hire. I distinguish two types: i) job-to-job transitions and ii) hires that experienced unemployment spell. Number of studies document growing training requirements in EE transitions.[12] Linked job-to-job hires are potentially those contacted by the employer due to their job- or industry-specific skills. Part time or seasonal jobs are excluded. Connected hire heterogeneity is examined with respect to entry wage premium, job tenure and hiring probability after firm closure. Remaining details on the empirical strategy of the worker side analysis are provided in the Appendix A.1.

The relation between entry wage and entrant characteristics is captured by the equation:

$$\begin{aligned} log(w_{ij}^E) = \alpha_0 + \alpha_1\ Connected_i + \alpha_2\ Jtj_i + &\alpha_3\ Connected_i \times Jtj_i \\ &+ \alpha_4 X_i + \alpha_5 W_j + \eta_j + \rho_t + \varepsilon_{ij} \quad , \end{aligned} \tag{1.1}$$

where i and j index respectively workers and firms, $Connected_i$ denotes connected hire, Jtj_i accounts for job-to-job transition, X_i captures worker and W_j firm characteristics, η_j is firm fixed effect and ρ_t time fixed effect. Each wage regression includes number of incumbents with whom the entrant is linked.

Firm Productivity

Let's consider firms that produce according to the following production function:

$$Y_j = f(K_j, L_j, M_j) = A_j[K_j^{\beta_K} L_j^{\beta_L} M_j^{\beta_M}]^{\alpha} \quad ,$$

where K, L, M are standard input factors (respectively capital, labor and raw materials), firms produce with diminishing returns to scale thanks to managerial component $\alpha < 1$ (in line with Lucas (1978)). A_j is firm-specific productivity which may be further

[12] See e.g. Cairo (2013a)

decomposed further into:

$$A_j = D_j e^{\beta_C log(C_j)} \quad .$$

Now, C_j denotes the part of productivity attributed to connected workers, whereas D_j is the part of TFP due to factors other than C_j. The above production function leads to the following empirical specification:

$$y_{jslt} = \beta_0 + \beta_K\, k_{jt} + \beta_L\, l_{jt} + \beta_M\, m_{jt} + \beta_C\, c_{jt-1} + X\,\delta + \eta_{st} + \mu_{lt} + \theta_j + \xi_{jslt} \quad , \tag{1.2}$$

lower case letters denote logarithms of production inputs and outputs, η_{st} industry-time fixed effects, μ_{lt} local labor market (hereafter LLM)-time fixed effects and θ_j firm specific productivity.[13] Note that the model includes lag of log connected hires, assuming that the effect on output and productivity does not appear instantaneously. To attenuate selection bias, the panel includes only firms that hire at least one worker in year $t-1$. One of the major concerns relates to possible selection of connected workers, as potentially only high productivity firms use co-worker network to high extent, or connected workers were particularly high skilled. The other caveat stresses the urge for time-varying productivity. To address the former, I include instrumental variable for the number of linked hires (c_{jt-1}). Olly-Pakes productivity analysis should target the latter, as it allows for the time-varying component of firm productivity. The analysis of informal links and firm time-varying productivity is performed in two stages: first, time-varying firm productivity (tfp_{jst}) is estimated using OP structural approach and then regressed on the log number of connected workers:[14]

$$tfp_{jst} = \gamma\, c_{jt-1} + W_{jt}\,\delta + \eta_{st} + \mu_{lt} + \theta_j + \xi_{jst} \quad , \tag{1.3}$$

where η_{st}, μ_{lt} and θ_j are the same as in equation 1.2 and W_{jt} includes firm control variables. Both output and productivity models control for the log number of hires in $t-1$.

Instrumental Variable

To address the possible endogeneity bias, I extend the analysis using instrumental variable approach. The major concern is that the hiring decision of each firm is endogenous. Another possibility is that firms that hire at least one worker in any given year are more pro-

[13]Note that equation (1.2) is the final form of the initial log transformation $y_{jslt} = \beta_0 + \beta_K k_{jt} + \beta_L l_{jt} + \beta_M m_{jt} + \beta_C c_{jt-1} + \zeta_{jslt}$, where β_0 and ζ_{jslt} are elements of $ln(D_j)$ denoting respectively the mean efficiency of firms across all industries and deviation from the mean of firm j in industry s, LLM l and time t. It can be further decomposed into productivity and random noise component $\zeta_{jslt} = \omega^*_{jslt} + v_{jslt} = \eta_{st} + \mu_{lt} + \omega_{jslt} + v_{jslt}$. In (1.2), θ_j describes firm time-invariant productivity and ξ_{jslt} contains both time-varying productivity and random noise.

[14]Where the model specification contains main production inputs and investment as a proxy for the TFP: $y_{jslt} = \beta_K k_{jt} + \beta_L l_{jt} + \beta_M m_{jt} + \omega^*_{it} + \xi_{jslt}$, where ω^*_{it} is time-varying unobserved firm productivity. OP method uses semiparametric methods to estimate unobserved productivity, where TFP is proxied by firm level investment decisions. For more information on the estimaton and moments see Appendix.

ductive and use referrals more frequently, what suggests the threat of pre-existing patterns in hiring.[15] Instrumental variable design exploits exogenous labor supply shocks within firm's own network generated by mass-layoffs. Our instrumental variable is defined as a number of workers from firm's co-worker network that were displaced by mass-layoff at $t-1$ in the industry different than firm j. The displaced workers are connected to the firm, what in turn can increase the chances of hiring through informal contacts.

Firm co-worker network is a collection of all former co-workers of incumbent employees. It is dynamic, as the set of incumbents and their former co-workers changes every year. Incumbent employees are defined as employees working in a given firm in the first week of January. Former co-workers are distinguished for past 5 years of incumbent's employment history. They need to have worked in the same establishment as incumbents (other than the current one), have employment spells longer than 3 weeks and spell overlap of at least one week.

Mass-layoffs provide exogenous shock in labor supply and are defined following Jacobson et al. (1993) and von Wachter et al. (2009).[16] Industry is defined on 2-digit level and social network of the firm at time t comprises employees' former co-workers that were employed at $t-1$.[17] Long-term unemployed, retired or missing records for co-worker network were discarded. Alternative specification of the instrumental variable defines it as a share of firm network size.[18] The log number of workers is more informative than the percentage, it brings also the information about the volume of the hires, crucial while studying output or productivity. Besides technical issues described in Section 1.5.4, the alternative instrumental variable does not change the results, which are provided in the Appendix A.6.

Event Study

In order to examine the dynamics of connected hires and its impact on firm productivity, I follow the approach proposed by Kline (2011). The regression is given by:

$$y_{jslt} = \alpha + \sum_{\tau} \beta_\tau D^{\tau}_{jt} + \beta_w W_{jt} + Trend_{st} + Trend_{lt} + \theta_j + \lambda_t + \xi_{jslt} \quad , \tag{1.4}$$

where the dependent variable is the log of productivity ($\ln(tfp_{jslt})$) or output of firm j that produces in industry s at time t in the local labor market l. Matrix of firm charac-

[15]If we assume that firms first observe worker productivity and, provided that she is of high skilled, ask her to refer some of her weak ties, the probability of a job opening/vacancy being referred through social network increases with the firm size.

[16]Mass layoffs take place if endogenous separation rate exceeds 0.33 in firms with more then 10 workers. Endogenous separation rate denotes the ratio of workers who were fired or quit during a quarter to the total amount of workers at the establishment at the beginning of the quarter.

[17]Different digit levels of variable *ATECO91* were distinguished, results remain valid for all of them.

[18]The total number of former co-workers of incumbent employees in past 5 years. All employees working in the first week of the given year are taken into account.

teristics (W_{jt}) includes its size, co-worker network, average wage and firm age, whereas remaining time-invariant features are captured by the firm fixed effect θ_j. $Trend_{st}$ and $Trend_{lt}$ are respectively industry- and LLM-specific time trends. The event study with output as a dependent variable additionally includes input factors (capital, labor, raw materials) as a control variables. D^{τ}_{jt} are "event time" dummies that take value 1 if the connected hire event is tau years away, defined as:

$$D^{\tau}_{jt} \equiv \boldsymbol{I}[t - e_j = \tau] \quad , \tag{1.5}$$

where $\boldsymbol{I}[\cdot]$ is an indicator function and e_j is the year of the event. In the estimation I examine three types of events, described in detail in Section 1.5.2. Given the equation 1.5, the coefficients β_τ capture the time path of productivity or output relative to the date of the event. In the estimation $\tau \in [-3, 4]$, where all observations more than 3 years before the event are assigned into time indicator "-3". Similarly, all observations more than 4 years after the event are assigned into time indicator "+4". Relatively small number of time indicators stems from the fact that our estimation sample contains observations between 1997 and 2001. Note that due to the binning of time indicators, discussing the treatment effect I focus on the "event time" coefficients $\tau \in [0, 3]$. I normalize β_{-1} to zero, so that all post-treatment coefficients can be thought of as treatment effects.

1.4 Data Description

1.4.1 Primary Data Sources

The analysis employs the administrative records from two provinces of Veneto, industrial region in northern Italy, obtained from *Veneto Workers Histories* (hereafter VWH) dataset. It contains yearly employer-employee observations and covers the period 1975-2001.[19] In case of migration into the other parts of Italy, the dataset keeps track of workers job performance. VWH provides information about the entire population of employed individuals and the entire population of firms in the two Veneto provinces with weekly frequency, and follows them in case of entry to establishments outside those two provinces. Besides information on total earnings, weeks worked, position or type of contract, VWH contains worker (gender, age, etc.) and firm characteristics (location, industry, closure, tax code, etc.). The industry is classified using 5-digit ATECO-91 code, set at the national level. Final worker sample contains private sector firm entrants in years 1995 - 2001 in the aforementioned provinces, part time or seasonal contracts are excluded, as well as hires

[19] VWH was kindly provided by *Fondazione Roberto DeBenedetti.*. VWH comprises the records for two Veneto provinces: Vicenza and Treviso. In case of change of the job outside those two provinces, VWH keeps the records, however one cannot retrieve the whole firm-employee population outside Treviso and Vicenza.

younger than 16 or older than 65.

The firm financial data *AIDA*, provided by Bureau van Dijk, contains records from the standardized reports that firms are obliged to submit annually to Italian Chamber of Commerce. It covers the years 1997 - 2001 for the whole population of firms in Vicenza and Treviso that hire between 2 and 600 employees and report annual sales above 500,000 euros. The variables describe balance sheet data: revenue, employment size, profit/loss, total assets, total value of production, total production cost, raw materials, wages, operating margin, value added and tax code.

1.4.2 Employer - Employee Matched Data

The merger of worker and firm financial datasets follows the strategy described by Card et al. (2014) with the tax code as the merge variable. The VWH and AIDA datasets overlap for 4 years between 1997 and 2001. The merge statistics are similar to Card et al. (2014): match rate of AIDA firms is 91% for the raw data and 96% for firms employing more than 15 workers.[20] Outliers in capital per worker and value added per worker were eliminated (at the 1^{st} and 99^{th} percentile level). Both datasets contain information on annual employment count in each firm. To avoid measurement errors, observations where the difference in employment level between two datasets exceeds 100 employees were discarded.[21] Correlation of the overlapping variables (employment size and wages) can be interpreted as a measure of validity of the merge. For the merge with firms that employ more then 15 workers they are 0.96 and 0.95 respectively.[22] For additional statistics and information on the matched dataset see Appendix A.2.1.

1.4.3 Sample Statistics

Connected Hires

The entire sample of hired workers contains 281,209 observations, whereas the productivity estimation sample includes 4,307 firm records. Table 1.1 presents characteristics of employees (Panel A) and firm hires (Panel B). Connected hires are on average older than non-connected ones, the share of female is smaller in the former group. Linked hires have on average higher entry wages, a sign of potential wage premium, documented previously in the literature. According to Panel B, around 11% of new hires were connected with

[20] The threshold is set as the firms with employment above 15 are exempt from many labor regulation regarding employment protection and trade unions (see e.g. Schivardi and Torrini (2008)).

[21] The number of observations with employment difference exceeding 100 is 108, 0.6% of the initial AIDA sample.

[22] For the sample of all merged firms the correlations are 0.96 and 0.32 for employment size and wages respectively. Wages in VWH dataset are measured annually, yearly employment size comprises all workers that worked in firm at the given year at least one week. The low correlation of wages for the whole sample may stem from the fact that in AIDA dataset the variable on wages contains also some overhead expenses.

Table 1.1: Basic characteristics of sample of entrants, years 1995-2001

Panel A: **Incubents and Hires**						
	Incumbents		**Hires**		**Connected Hires**	
Worker characteristics:	Mean	SD	Mean	SD	Mean	SD
Age	33.6	10.1	30.4	9.39	32.7	9.47
Female	0.42	0.49	0.32	0.47	0.30	0.46
Wage (log, weekly)	6.43	0.50	6.35	0.38	6.42	0.39
N	756,148		281,209		39,369	

Panel B: **Hires - Firm Side**						
	Connected (%)		**Job-to-job** (%)		**J-t-j Connected** (%)	
Firms:	Mean	SD	Mean	SD	Mean	SD
All	11.18	21.25	46.99	35.54	7.81	17.84
>100 workers	19.30	18.01	52.87	23.25	13.57	15.01
∈(20,100] workers	12.73	20.76	48.33	31.79	8.97	17.59
≤20 workers	8.37	21.67	44.75	40.20	5.74	18.15
Large Cities	10.36	22.13	46.33	37.45	6.99	18.59
Medium Cities	10.41	20.69	46.63	36.59	7.61	18.10
Small Cities	11.48	21.30	47.15	35.03	7.95	17.69
Industrial Districts	14.67	23.77	48.29	35.57	10.81	20.98
Manufacturing	12.04	21.17	47.48	34.21	8.46	17.87
Services	9.43	20.26	48.95	37.33	6.82	17.66
N	1,479		3,400		1,165	

NOTE: Panel A presents characteristics of population of workers, whereas Panel B presents characteristics of hires for the population of firms ($N = 4,307$). The N in Panel A displays number of individuals, not obervations, since one individual can be a hire more than once over the period 1995-2001. The city types were distinguished based on the distribution of number of inhabitants in the sample. Large cities are the ones above 80,000 inhibitants, medium comprise cities between 20,000 and 80,000 inhabitants, whereas small ones have less than 20,000 citizens. Variable N in Panel B describes number of firms with positive number of hires in each respective category.

any of the incumbents, the number that corresponds to previous findings (HS claim that 12% of entrants were linked, Eliason et al. (2018a) find 10.7%).

Some interesting patterns are revealed by Panel B of Table 1.1. The share of job-to-job transitions among linked hires is higher than in the entire population of hires (70% compared with 47% in the entire sample of hires). The linked hires prevail in large establishments, accounting for nearly 20 percent of all hires. Similarly for job-to-job and

Table 1.2: Basic characteristics of employer-employee matched dataset, years 1997-2001

	All	**Non-connected**	**At least one connected**	**>20% Hires connected**	**>50% Jtj connected**
Size	44.94	32.41	68.58	61.73	65.21
	(53.63)	(30.53)	(72.44)	(71.23)	(74.68)
Firm age	13.37	13.01	14.05	13.91	14.34
	(8.02)	(7.87)	(8.24)	(8.34)	(8.39)
Avg. wage	14.35	14.22	14.61	14.56	14.81
(annual, in 1,000 euro)	(5.53)	(5.08)	(6.28)	(5.54)	(5.82)
Revenue/Worker (log)	4.89	4.92	4.83	4.85	4.89
	(0.72)	(0.74)	(0.68)	(0.69)	(0.69)
Profit/TotalAsset	0.02	0.02	0.02	0.02	0.02
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Profit/Worker	2.66	2.64	2.69	2.80	3.01
	(8.93)	(9.34)	(8.11)	(8.16)	(8.72)
N	4,307	2,828	1,479	1,034	804

NOTE: The above table provides statistics for the merged employer-employee dataset. All samples contain firms that in the given year hired at least one worker. Among them non-linked denotes only those firm-year observations where none of the new hires was linked, third sample includes observations where among new hires at least one was linked. Similarly the fourth column contains obs. where at least 20% of new hires were linked, the last sample considers obs. there more than 50% of new hires were job-to-job linked.

connected job-to-job hires. When it comes to the geography of connected hires there are no substantial differences depending on the size of the city. The differences arise for the industrial districts, defined as the clusters of firms with particular economic specialization in distinctive geographical areas. Higher incidence of connected hires within industial clusters serves as a motivation for the study of the role of co-worker connections within industrial clusters.

Productivity and Hiring Patterns

The final sample contains only 'hiring' firms. The hiring is an endogenous decision, hence it is important to study the firm-level characteristics (employment, firm age, productivity) and check for any pre-existing patterns. Table 1.2 provides firm characteristics of hiring firms, depending on the extent to which firms exploit informal contacts in hiring decisions. For most of the financial variables, such as revenue per worker and the share of profits in total assets, one can distinguish small differences between the samples. The differences in revenue per worker do not exceed 9 log points, with lower values reported by the firms with higher share of socially connected hires. The average wage increases with the use of co-worker links, however it is a consequence of surge in the firm size. Profits per worker follow similar pattern, however scatter plots in Appendix A.2.1 show no clear relationship between percentage of linked hires and pre-existing financial balance sheet characteristics. Positive relationship between firm size and the use of referrals contrasts with findings of Rebien et al. (2017). Note however, that our final sample does not include firms with less than 15 workers, what may explain the differences.

1.5 Empirical Results

1.5.1 Referral Heterogeneity

The estimates presented in Table 1.3 indicate the advantage of job-to-job linked hires both in entry wage premium (Panel A) and the length of job tenure (Panel B). Entrants who shared working history in past 5 years with any of the incumbents have on average 2.9% higher initial salary, what corresponds to the initial wage premium of linked hires of 3.6% reported by HS. Job-to-job transitions provide advantage of 9.4%, hence job-to-job linked entrants receive higher entry wages than any of the reference groups.[23] The advantage of job-to-job linked hires appears also in job tenure duration analysis (Panel B of Table 1.3). They are less likely to exit the firm than any other reference group. Additionaly, high number of former co-workers among incumbents induces longer tenure, a sign of a peer pressure of the network.

The analysis of firm closures confirms that linked job-to-job workers in the exiting firm have higher probability of finding a job within first 26 weeks after displacement (Table A11). The results are robust to different model specifications and inclusion of instruments and control variables. All of these suggests the importance of job-to-job transition for linked hires, pointing at possible transmission of job- or industry-specific skills.

1.5.2 Firm Productivity

Baseline Analysis

Using the identification strategy described in Section 1.3.2, I examine the impact of the share of connected hires on firm output and productivity. Table 1.4 presents the main results, both for the output model of equation 1.2 and two stage productivity estimation with the use of OP semiparametric model, as in formula 1.3. For now we are interested only in one year lag of linked hires, further part will examine the dynamics of the effect

[23] Reference groups are linked job-to-job (12.3% higher initial weekly wage), linked with unemployment spell (2.9% advantage), non-linked job-to-job (9.4% advantage) and non-linked with unemployment spell.

Table 1.3: Entry wage regression and job duration (Cox Proportional Hazard Model), VWH 1995-2001.

	(1)	(2)	(3)	(4)
		Panel A. Entry wage		
Connected	0.029***	0.029***	0.028***	0.055**
	(0.002)	(0.003)	(0.002)	(0.025)
No. of connections	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Jtj	0.094***	0.094***	0.114***	0.114***
	(0.001)	(0.001)	(0.001)	(0.002)
Jtj × *Connected*		0.000		-0.026
		(0.003)		(0.025)
Short spell			0.044***	0.044***
			(0.002)	(0.002)
Short spell × *Connected*				-0.027
				(0.025)
R^2	0.58	0.58	0.58	0.58
		Panel B. Cox Proportional Hazard Model		
Connected	0.86***	0.88***	0.86***	0.88***
	(0.014)	(0.021)	(0.014)	(0.027)
No. of connections	0.99***	0.99***	0.99***	0.99***
	(0.001)	(0.001)	(0.001)	(0.002)
Jtj	0.65***	0.65***	0.56***	0.57***
	(0.007)	(0.007)	(0.007)	(0.007)
Jtj × *Connected*		0.95*		0.95
		(0.030)		(0.035)
Short spell			0.72***	0.72***
			(0.101)	(0.011)
Short spell × *Connected*				1.03
				(0.048)

NOTE: Sample is of the size: N = 281,209. Control variables contain age, age^2, gender, residence, position on the worker side; province, size, firm and industry-year fixed effects. Column (4) includes additionally interaction term *Long spell* × *Connected* for identification purposes. Dep. variable $log(w_{ij}^E)$ is winsorized at 1^{st} and 99^{th} percentiles. Panel B. does not include firm fixed effects and industry-year fixed effects, controlling only for industry. Proportional Hazard model is right censored. Job tenure is measured in weeks. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

of connected hires on firm productivity and output. Table 1.4 includes three model specifications: the baseline (denoted as OLS), first difference and the instrumental variable. *Connected* and *Hires* are lagged variables describing log of inflow of linked workers and

Table 1.4: Productivity and output analysis, 1997-2001.

	Productivity			**Output**		
Model:	OLS	Δ	IV	OLS	Δ	IV
$Connected_{-1}$	0.061**	0.046*	0.100*	0.057**	0.045*	0.120**
	(0.027)	(0.026)	(0.054)	(0.026)	(0.025)	(0.073)
$Hires_{-1}$	0.013**	0.009*	0.023***	0.014***	0.010*	0.025***
	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.008)
$Connected_{-1} \times Hires_{-1}$	-0.019**	-0.014	-0.060*	-0.019**	-0.014	-0.070**
	(0.009)	(0.009)	(0.034)	(0.009)	(0.009)	(0.033)
$log(K)$				0.14***	0.10***	0.13***
				(0.019)	(0.021)	(0.021)
$log(L)$				0.18***	0.21***	0.22***
				(0.022)	(0.024)	(0.024)
$log(M)$				0.39***	0.37***	0.38***
				(0.014)	(0.015)	(0.014)
F-stat 1st stage			445.3			444.9
R^2	0.93	0.07	0.93	0.98	0.46	0.98

NOTE: Estimates taken from specification of form given in Equation (1.3) where the dependent variable is either $\ln(tfp_{jilst})$ (Productivity) or $\ln(y_{jilst})$ (Output). Size of the sample for OLS and IV analysis is 4,307, for $\Delta\, n = 1,705$. The model Δ denotes the OLS regression of the output or productivity yearly differences, measuring their surge due to referrals. The model includes differences of input factors, connected hires, hires, their interaction, LLM-year and industry-year fixed effects. Remaining models include all of the aforementioned fixed effects as well as production inputs (in Output), firm fixed effects and firm characteristics (employment count, average wage, firm age, co-worker network size). Variable $Connected_{-1}$ denotes log number of connected hires at $t-1$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

all hires.

Indeed, the hire of linked workers has positive impact on firms productivity and output. More precisely, 10% increase in the number of linked hires increases firm's productivity by approximately 1%.[24] Similar effect can be found for the output. The negative sign of interaction term is quite surprising, relating possibly to positive employment shock that may resolve after firm's activity suspension or periods following mass employment reduction. Reassuringly, the IV results are close to those of OLS in terms of the magnitude. The first stage $F-statistics$ and R^2 indicate strong correlation between number of linked workers hires at time t and the number of employees former co-workers who experienced mass-layoff at time $t-1$. Similar relationship between displacement of connected workers and connected hires can be established using event study model, similar to the one introduced in equation 1.4. In this case our dependent variable is the number of

[24]The calculations follow the formula $log\left(\frac{E[y|X_1=x_1,X_2=1.10x_2]}{E[y|X_1=x_1,X_2=x_2]}\right)$ with mean value of *Hires* of 1.14.

Table 1.5: Impact of number of connected hires on firms' productivity and output - event study.

Panel A: **Productivity**			
Event:	$\tau \in [0,1]$	$\tau \in [2,3]$	$\tau \in [0,3]$
Baseline	0.038**	0.045	0.042*
	(0.017)	(0.029)	(0.022)
Connected Hire Shock	0.033*	0.041	0.037*
	(0.019)	(0.030)	(0.022)
Connected Worker Displacement	0.075***	0.152***	0.113***
	(0.019)	(0.038)	(0.028)
Panel B: **Output**			
Event:	$\tau \in [0,1]$	$\tau \in [2,3]$	$\tau \in [0,3]$
Baseline	0.016***	0.024***	0.020***
	(0.004)	(0.007)	(0.005)
Connected Hire Shock	0.011**	0.014*	0.013**
	(0.006)	(0.008)	(0.007)
Connected Worker Displacement	0.028***	0.052***	0.040***
	(0.005)	(0.009)	(0.006)

NOTE: Note: Estimates taken from specification of form given in Equation (1.4) where the dependent variable is the number of patents applications. The sample size is $4,676$ ($1,364$ firms). Sample includes only firms with more than 2 observations. The model includes year and firm fixed effects, industry trends and LLM trends, network size, number of hired workers, firm size, average wage and firm age. Numbers in parentheses are standard errors clustered at the LLM level. $\tau = [a,b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. $*p < 0.1$, $** \; p < 0.05$,$*** \; p < 0.01$.

connected hires, whereas the event is the first time someone from firm's network becomes displaced during mass-layoff. The results are presented in Figure A6. There is no clear trend prior to the event for both connected and market hires. At the year of displacement there is a significant increase in connected hires with no effect on market hires. There is no "crowding-out" effect of connected hires on the market ones. Firms are using increased capacity to hire through their own co-worker network.

Event Study

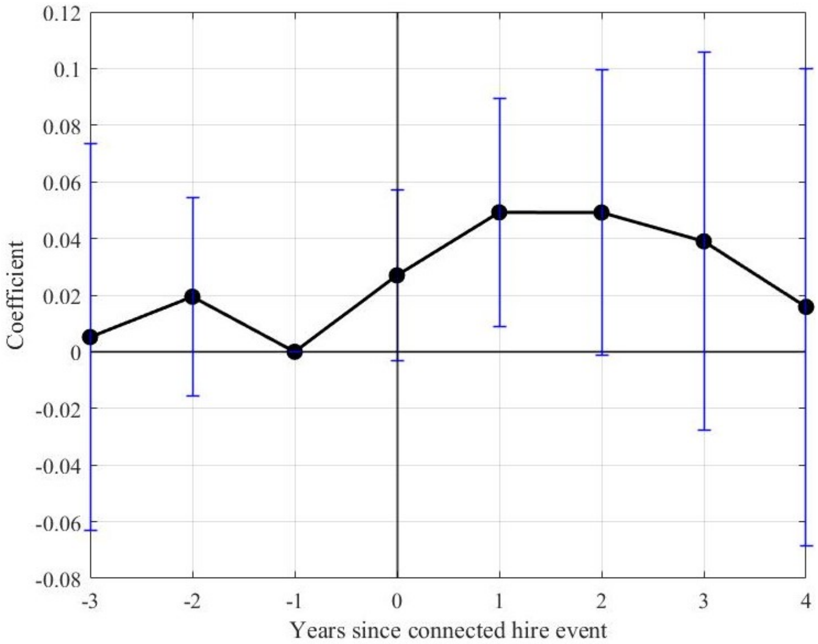
Table 1.5 presents the dynamics of the impact of connected hires on firm productivity using the framework described in Section 1.3.2. Three events are considered: $i)$ Connected Hire (Baseline) $ii)$ Connected Hire Shock and $iii)$ Connected Worker Displacement. The first event denotes the year in which for the first time in the sample firms hire a connected worker. The second event marks a year in which annual increase of employment exceeds 20% and at least 20% of the new hires were connected. The third event happens when for the first time within firm co-worker network there is a positive number of displaced workers. In other words, it is the first time at which firm has at its disposal connected, displaced worker. It uses labor supply shock and hence can be treated as an IV-type of event, where event marks "intention" to treat. The estimation sample contains both treated and never-treated groups that are observed for at least two years. Note that the estimation sample of event study changes with respect to baseline one. In a pursue to gain more information, I include also observations for the years when the firms didn't hire any worker.

To increase statistical power Table 1.5 tests the hypothesis about the average of β_τ coefficients for particular time intervals. Note that the matched dataset is a short panel, what limits the study of long-run effects of the event. The event time indicators are binned at "-3" and "+4" level. Therefore, Table 1.5 uses only the estimates between 0 and 3 years after the event. As expected from the baseline analysis, the estimates for the contemporaneous effect ($\tau \in [0, 1]$) are significant for all types of events. The short-run effect ($\tau \in [2, 3]$) differs between the events, however the average effect ($\tau \in [0, 3]$) remains significant. The third row of Table 1.5 corresponds to Figure 1.1 (b). The estimated average increase over the first three years after the event 0.113 and significantly different than zero. Such surge in productivity is equivalent to a 0.29-standard-deviation increase.[25] As expected, the effect on output (Panel B) is much stronger for all event types and does not wane in the short run.

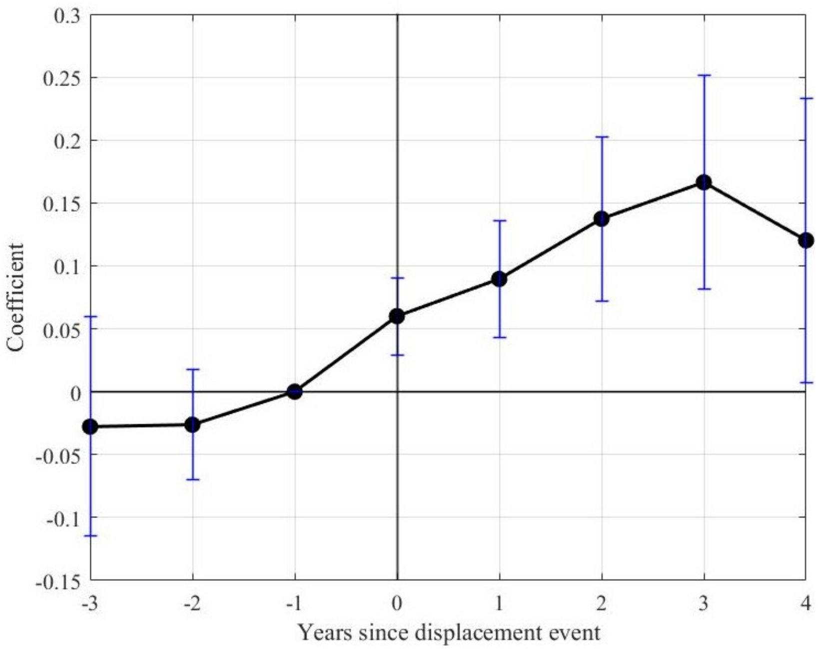
Figure 1.1 displays the estimates of the event study analysis for Connected Hire and Connected Worker Displacement event. For both event types there is no clear trend prior to the event data, the estimates remain close to zero. The effect of connected hires on productivity is the highest in the year following the event, whereas for the connected worker displacement reaches the peak is in the third year after the event. The reason for that shift lies in the dynamics of hiring process: the first event measures directly the year of hire (at time 0), whereas the latter captures the labor supply shock within firm's network, an "intention" to treat. From Figure A6 we know that increase in displaced connected workers leads into the surge of connected hires, however, the latter may be lagged with respect to the displacement event by several months, shifting the time path to the right. The dynamics of the effect of connected hires on productivity and the estimates

[25] Standard deviation in the sample of never-treated in thirs event is 0.386

Figure 1.1: Firms' Productivity, Relative to the Year of a Connected Hire and Connected Worker Displacement.



(a) Connected Hire



(b) Connected Worker Displacement

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent robust confidence intervals.

at the year of the event may help to explain why Eliason et al. (2018a) do not find any contemporaneous effect.

Connected Worker Displacement event uses the exogenous labor supply shocks, however, to obtain instrumental variable estimates I modify the design of the event study. I introduce the dummy variable that takes value one in each year after the connected hire event and then instrument it with the dummy variable that takes value one each year after the connected worker displacement event and zero otherwise.[26] The connected hire and connected worker displacement dummies take value 1 only within 4 years after the event. Table A22 displays the 2SLS estimates of the model. As expected, the first stage estimates remain significant at 1 percent level, similarly for the estimates of connected hire.

1.5.3 Industrial Districts

Veneto is a highly industrialized region (textile, furniture, machine and leather production) with a number of industrial districts, clusters of firms with particular economic specialization in distinctive geographical areas. The geographic and industrial proximity may facilitate the diffusion of information and networking, leading to increased reliance on informal hiring channels. Connected hires within industrial districts additionally transmit industry-specific human capital what may have an effect on firm productivity. *Istat*, based on local labor markets (Sistemi Locali del Lavoro) and survey of economic units, distinguishes 141 industrial districts in Italy. In total, industrial districts account for nearly a quarter of employment (24.5%), two most industrialized regions of Lombardy and Veneto employ 60.4% of industrial district workforce (respectively 33.7% and 26.7%).[27]

The region of Veneto has 22 Industrial Districts, 9 of them are in the provinces of our interest - Treviso and Vicenza. Employment in those industrial clusters accounts for on average 9.71% of employment in Treviso and Vicenza provinces over in years 1997-2001, 10.26% of all hires in those two provinces are generated by firms within industrial districts. Table A6 presents basic characteristics of industrial districts in Veneto. Interestingly, in the local labor markets containing industrial districts the percentage of linked transitions is almost the same as on average (11.23% compared to 11.18% in the entire sample), whereas 14.67% hires of firms in industrial clusters are connected. The share of linked hires increases further for the flows within industrial clusters (both previous and new firm are within the same industrial district), where even 25.63% of firm entrants are connected. The higher numbers within industrial districts support the intuition of higher reliance on informal contacts while hiring in specialized clusters of firms.[28] The within

[26]Formally, the model takes form $y_{jslt} = \alpha + \beta_h\, Connected\ Hire_{jt} + \beta_w\, W_{jt} + Trend_{st} + Trend_{lt} + \theta_j + \lambda_t + \xi_{jslt}$., where $Connected\ Hire_{jt}$ is a dummy variable that takes value one within 4 years following the connected hire event. I instrument it with $Displaced_{jt}$ - a variable that equals one within the first 4 years after the connected worker displacement event.

[27]For the formal definition of industrial districts and basic statistics look at *Istat* website: https://www.istat.it/it/files//2015/02/EN_Industrial-districts.pdf

[28]This claim was also checked formally using logit model.

industrial districts hires are 35.69% of hires in those clusters and 3.66% of all hires in two provinces of Veneto region. Along with co-worker links, the percentage of job-to-job and linked job-to-job transitions increases significantly among within industrial district hires. Increase of EE and linked transitions may indicate that firms within industrial clusters to higher extent use referrals to attract more productive workers.

To test that conjecture, I first focus on the worker side. The job transitions within industry clusters are defined as those where both previous and current firms are in the same industrial district and transition didn't involve a change of industry. Table 1.6 Panel A reports the entry wage results using the specification outlined by equation 1.1. The fact that hire took place in local labor market with industrial district does not impact the wage of hires. What is important is the fact that the hire was within industrial cluster. Firm entrants that come from the same industrial districts and industry have 2.7% higher entry wage, whereas linked firm entrants within industrial cluster hires experience 5.4% wage premium with respect to the reference group: non-linked outside industrial district hires. More interestingly, this effect comes from job-to-job linked transitions. Column (5) of Panel A indicates that connected, within industrial district, job-to-job hires have around 14.8% wage premium, whereas those who were connected, transitioned within the cluster and experienced unemployment spell have significantly lower entry wage than their connected counterparts from the outside of the industrial cluster (0.2% compared to 2.7% wage premium).[29] Comparing with more general results of Section 1.5.1, not only job-to-job linked hires are more frequent in those areas, but also entry wage premium is around 2.5 p.p. higher than outside industrial clusters.

Connected hires within industrial districts may bring to the new firm some industry-specific human capital. As the frequency of such transitions is significantly higher within industrial cluster hires, they may have impact the firm output and productivity. Firm productivity framework introduced in Section 1.3.2 allows to distinguish additional effect for within industrial district hires by including in models (1.2) and (1.3) log number of connected hires within the same industrial cluster at $t-1$. Limiting the sample only to firms operating in industrial clusters narrows it to 498 observations, too few to obtain reliable estimates. Table A24 does not find any additional effect for linked hires within industrial clusters both for output and productivity. One should however interpret that with caution given limited number of establishments within industrial clusters in two provinces of Veneto. The issue requires larger sample of firms, ideally from the whole Veneto region.

[29] Keep in mind that the reference point of Panel A column (5) are non-linked, non-jtj, outside industrial district hires.

Table 1.6: Entry wage regression - Industrial Districts and Industry-Specific Human Capital, 1995-2001

Dep variable: $log(w_{ij}^E)$	(1)	(2)	(3)	(4)	(5)
			Panel A: **Industrial Districts**		
Connected	0.029***	0.026***	0.026***	0.027***	0.027***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Jtj	0.094***	0.094***	0.094***	0.094***	0.094***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ind. District		0.060	0.051	0.051	0.051
		(0.067)	(0.061)	(0.067)	(0.067)
Within Ind. District			0.027***	0.030***	0.027***
			(0.004)	(0.004)	(0.006)
With. Ind. Distr × *Connected*				-0.013*	-0.025**
				(0.007)	(0.012)
With. Ind. Distr × *Connected* × *Jtj*					0.018
					(0.014)
R^2	0.58	0.58	0.58	0.58	0.58
			Panel B: **Industry-specific Human Capital**		
Connected	0.029***	0.025***	0.019***	0.022***	0.025***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Jtj	0.094***	0.092***	0.092***	0.091***	0.091***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Same industry		0.039***	0.038***		
(1-digit)		(0.001)	(0.001)		
Same industry× *Connected*			0.008**		
(1-digit)			(0.004)		
Same industry				0.053***	0.054***
(3-digit)				(0.001)	(0.001)
Same industry× *Connected*					-0.006*
(3-digit)					(0.003)
R^2	0.58	0.58	0.58	0.58	0.58

NOTE: Estimates taken from specification of form given in Equation (1.1) Sample is of the size: n = 281,209. Control variables contain age,age^2, gender, residence, position on the worker side; province, size and firm fixed effects. Dep. variable $log(w_{ij}^E)$ is winsorized at 1^{st} and 99^{th} percentiles. Reference group for Panel A column (4) are non-within cluster, non-link hires, whereas in Panel A column (5) those are non-within ind. distr, non-link and non-jtj hires. For identification purposes regression in A column (5) contains also *Within Ind. Distr*× *Jtj* variable, not reported in the table. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

1.5.4 Extensions

Industry-Specific Human Capital

One of the threats to identification of the co-worker network effect is the industry-specific human capital. By not including the controls for the same industry job transition, the connected hire variable may account for the former effect. Sharing employment history with any of the incumbent workers increases probability that the hires worked previously in the same industry as the one of the firm which they enter and hence the variable *Connected* may account for industry-specific skills of workers. To test that hypothesis I modify the entry wage framework from Section 1.3.2 by including dummy variable that takes value one if the industries of the origin and entry firm are the same (at either 1-digit or 3-digit levels) and its interaction with number of connected hires. Statistics presented by Table A4 confirm the intuition - connected hires more often come from the same industry than non-linked ones, both on 1- and 3-digit levels. Moreover, they have significantly more labor market and industry experience (at 1-4 digit levels).[30] Panel B of Table 1.6 presents the estimates. As expected, not accounting for industry-specific skills overestimates the impact of co-worker links, however the bias is not large. In the most conservative specification (column (3)), the estimates of wage premium of connected hires are 1 p.p. lower than in the baseline case (column (1)). Workers from the same industry on more detailed level (3-digit) receive higher entry wage premium than in more general specification (column (3)). Interestingly, on 1-digit industry level there is premium for linked workers from the same industry. Effect of co-worker links remains robust in all of the cases, hence entry wage premium for connected workers does not come entirely from industry-specific human capital.

Similarly to the case of Industrial Districts, I study the impact of same-industry linked hires on firm productivity and output. Including log number of connected same-industry hires in Table A24 changes the baseline productivity results. As a result, *Connected* $\times$ *Same Ind.* seizes the estimates of *Connected*, leaving the latter insignificant. It indicates the channel through which referrals give surge to firm productivity - industry-specific human capital. Firms may use co-worker links to target workers with more industry experience and increase significantly their output and productivity. Both sample statistics and firm side analysis support that conjecture.

Other Specifications

One of the caveats of productivity model specification is the measure of connected hires. The main advantages of log number of linked workers used in previous section is its simplicity and the fact that it captures the number of linked hires and skills or knowledge

[30] For more statistics on same industry hires see Table A5

that they bring. The alternative measure of connected hires, defined as their share among all hires at time $t-1$ does not identify the volume effect. Depending on the size of worker inflow, even small number of linked hires can account for a significant share of new hires if the number of entrants to the firm is small. Conversely, if some year employer decides to increase number of workers by significant amount, however referred ones constitute only a small fraction, we loose their impact, regardless of their comparative advantage. The measure would be valid provided that connected workers affect firm's productivity only if they account for a large fraction among new hies. The alternative approach looks at the share of newly hired connected workers in firm's total employment. To omit the collinearity problem the log employment is excluded from the model and the dependent variable defined as an output per worker. Having dependent and independent variable as a function of the same variable infringes model validity. Remember, however, that in the matched data one can observe the employment both in worker and firm data. To restore the validity of the model I use the firm side employment to compute output per worker and VWH firm size to construct share of newly hired linked entrants in firm's total employment.[31] I attribute each variable of interest, the employment from their original dataset.[32] The results of productivity analysis presented in Table A9 show that under previously describes specification main findings remain unchanged.

1.5.5 Placebo and Robustness Checks

Placebo

One could argue that given the baseline specification (1.3), firms with high employment have large former co-worker network, what leads to higher number of displaced employees among them. At the same time large firms are typically more productive ones. The correlation between firm size and co-worker network is not strong, takes value of 0.42. Additionally, the inclusion of firm fixed effects eliminates unobserved heterogeneity within them. The unobservables may include also match specific elements that relate to new hires. Imagine that thanks to e.g. innovations and technology, unemployed and employed workers who search on-the-job have better information about particular position they apply for. Then the rise in firm productivity may not be driven solely by a distinctive features of connected workers, but reflect better worker-firm matches. Despite including in the model log number of lagged hires, number of linked workers may convey the effect of increased match quality.

To test that possibility, in the spirit of Balsvik (2011) I include log number of non-

[31]Formally equation (3) takes form $\widetilde{y}_{jslt} = \beta_K k_{jslt} + \beta_M m_{jslt} + \beta_R \widetilde{c}_{jt-1} + \beta_0 + X\delta + \eta_{st} + \mu_{lt} + \theta_j + \xi_{jslt}$ with $\widetilde{y}_{jslt} = \frac{y_{jslt}}{l^1_{jslt}}$ and $\widetilde{c}_{jt-1} = \frac{c_{jt-1}}{l^2_{jslt}}$, where l^1_{jslt} is log employment size of firm j at time t taken from AIDA dataset, whereas l^2_{jslt} denotes log employment derived from VWH.

[32]Both revenue and l^1 come from AIDA dataset, whereas r and l^2 come from VWH.

linked new hires at $t-1$ along with linked ones in the model 1.2 and 1.3. The results (see Table A7) show that the number of non-linked workers does not impact the results and the findings of the baseline model remain valid, regardless of the specification.[33] Second type of placebo test checks the log number of lagged non-linked new hires as a substitute for the linked ones.[34] If in fact workers and firms are better match non-linked, new hires should also contribute to firm productivity. Table A8 shows that that's not the case. The third placebo check relates to event study framework. The Connected Hire and Connected Hire Shock events are replaced by Non-Connected Hire and Non-Connected Hire Shock events. Neither of the checks show any impact of non-connected hires on firm productivity (see Table A10 and Figure A3).

Robustness

To examine the robustness of the results, all models are subject to the validity checks that either use subsamples of the estimation sample or add some additional control variables. The estimation sample is grouped with respect to gender, industry, occupation and tenure for worker side. Additional control variables include worker and firm characteristics as well as displacement shock in the same year, province and province$\times$ industry. In case of productivity analysis the samples are chosen according to industry, employment size, gender proportions, firm age, location and percentage of blue collar workers. Furthermore, productivity gains are distinguished only for good firms, where the latter are defined using standard AKM fixed effects. In all of the settings main results remain valid, despite some differences in magnitude. All results are presented in Appendix A.6.

1.6 Conclusion

Growing number of works in network and referral literature report how co-worker network facilitates job transitions and provides the advantage at a hiring stage. It is widely documented that workers who obtained job thanks to informal contacts have initially higher wages and lower turnover, what complies with seminal work of Montgomery (1991), who claims that referred workers are mostly high productivity ones, as a result of network inbreeding. In this framework referrals are not only a way of omitting adverse selection problem at the hiring stage, but potentially contribute to firm productivity and output.

This paper is the empirical attempt to answer the questions of socially connected hires heterogeneity and the consequences of using informal contacts for the hiring firms. For that purpose, I construct matched employer-employee data from the region in northern

[33] Although usually with positive sign. For the results see Appendix A.3

[34] The model specification is $y_{jslt} = \beta_K k_{jt} + \beta_L l_{jt} + \beta_M m_{jt} + \beta_R nc_{jt-1} + \beta_H h_{jt-1} + \eta_{st} + \mu_{lt} + \theta_j + \xi_{jslt}$, where nc is number of non-linked and h number of all hires at time $t-1$.

Italy and use co-worker links as a proxy for referrals. Heterogeneity within connected hires originates from the unemployment spell before a job entry. Connected job-to-job hires are advantaged at every stage of their tenures, compared with linked hires who experienced unemployment spells. Detailed firm financial data allows to estimate the impact of connected hires using structural productivity estimation model. I find that the lagged number of connected hires increases significantly firm productivity and the effect may last up to three years following the hire. Connected hires inflate firm productivity through transfers within the same industry, suggesting that firm co-worker network may facilitate the transmission of job- or industry-specific knowledge. The findings are robust to subsequent checks and the instrumental variable that employs firms' co-worker network and labor supply shocks generated by mass displacements. The findings open a discussion about the role of co-worker networks in transmisson of skills or knowledge diffusion, a topic that deserves further study.

Chapter 2

Inventors' Coworker Networks and Innovation

written jointly with Sabrina Di Addario and Michel Serafinelli

2.1 Introduction

A prominent feature of the labor market in many developed countries is the tendency for firms to hire using social connections (Pellizzari, 2010; Burks et al., 2015; Dustmann et al., 2016; Hoffman, 2017). Nevertheless, we have limited knowledge regarding the extent to which available connections impact plants' innovation.

This is the first paper to present direct evidence on the extent to which plants' innovation is affected by access to knowledgeable labor connected through the co-worker network. In confronting the non-trivial measurement challenges involved, we take advantage of a unique dataset that matches administrative employer-employee records from north-central Italy to patent data.

While the mechanisms we document may apply to other workers and other outcomes as well, we focus here on inventors and patenting because innovation is considered to feature especially sizable positive social spillovers and is generally regarded as a key driver of economic growth (Bloom et al., 2013; Bell et al., 2019). Moreover, albeit inventors are not the only workers who may transfer relevant information from one plant to another, they undoubtedly have large potential to do so.

Our empirical strategy exploits plant closures where displaced inventors are connected to other plants because of former co-workers. The co-workers connections generate a plant-specific shock to the supply of knowledgable labor, by directing the supply of displaced inventors toward the connected plants. The outcome of interest is plants' innovative activity; therefore we take a patent application as a signal of the presence of some innovative output (Lotti et al., 2005). We provide two sets of estimates. First, we estimate event-study models where the treatment is the displacement of a connected inventor. We estimate our econometric model with and without the never treated plants; in the latter case identification comes from the differential timing of treatment onset among the treated plants. [1] Second, we estimates IV specifications where we use the displacement of a connected inventor as instrument for the hire of a connected inventor. This analysis assumes that the whole impact of the displacement of a connected inventor is mediated by a connected inventor hire. A potential identification concern arises if the directed shocks to the supply of knowledgeable labor also pick up market-level supply shocks or demand shocks. [2] We do not expect this to be a major factor in our context. The sample comprises mostly closures of small to medium-size plants for which the market effects are likely to be small - the median closing plant has around 100 employees. To explore this possibility further we control for displacements in the same local labor market x industry. We also perform a "placebo"-type analysis, exploiting the displacement of inventors with connections to plants in same local labor market x industry.

Even though the issues analyzed in this paper are of general interest, the specific case of north-central Italy is also important. The macro-region we analyse (which includes Emilia-Romagna, Friuli-Venezia Giulia, Marche, Toscana, Trentino-Alto Adige, Veneto) is an economic area where specialized producers, frequently organized in districts, have been effective in promoting and adapting to technological change during the past four decades. This so called 'Third Italy' has received a good deal of attention by researchers, both in Europe and in the United States. (Brusco, 1983; Piore and Sabel, 1984; Trigilia, 1990; Whitford, 2001; Piore, 2009). Given Third Italy industry mix, discussed in Section 2.2, our findings are particularly relevant for manufacturing regions such as Germany's Baden-Wuerttemberg and the British Motor Valley.

Our empirical evidence can be summarised as follows. We document that following displacements within a plant's network there is a significant increase in the hiring of connected inventors. Moreover, and most importantly, the improved capacity to employ knowledgeable workers increases plants' patenting activity. Specifically, in the event-study, the estimated average change over the four years starting with the year of the connected inventor displacement is an increase between 0.17 and 0.22 standard-deviations.

The IV estimates indicated the the effect of the hire of a connected inventor is an increase in patents application of 0.5, equivalent to a 1.56-standard-deviation increase. The hire of a connected inventor is a major event for these plants, and we find this implied shift large but not unrealistic. Further, a decomposition of the patent increase suggests that the additional output is a combination of patents authored by the newly hired connected inventors (either solo-authored or with co-authors outside the receiving plant), patents resulting from a collaboration among the hired connected inventors and other workers

[1] Our identification strategy draws on the one in Eliason et al. (2018a).

[2] See Gathmann et al. (2020) and Cestone et al. (2016)

within the receiving plants, and patents authored by the other workers within the new plants (without the hired connected inventors).

Our work is linked to several literatures. First, our paper is linked to studies of information transmission through networks (De Giorgi et al., 2020; Schmutte, 2015; Battisti et al., 2016; Caldwell and Harmon, 2019), and in particular of co-worker networks in the context of displacements: Cingano and Rosolia (2012), Glitz (2017), Saygin et al. (2019), Dalla-Zuanna (2020), all document, for instance, a significant, positive relation between network employment rate and the probability of finding a new job.[3] Closely related is the study of Eliason et al. (2018a) who, using Swedish register data, document a positive effect of social connections on firm's total hires, job separations, and production. In a similar vein, Korchowiec (2019) shows that hires from a firm's own network increase significantly its productivity.[4]

Our study also contributes to the body of work analysing R&D spillovers, and in particular the consequences of mobility of R&D personnel.[5] For instance, Fons-Rosen (2013) finds that foreign direct investment has a greater impact on the host economy in terms of knowledge diffusion when firms reallocate inventors from the already established R&D labs in their home country to the newly developed ones in the host country. Maliranta et al. (2009) find that firms involved in non-R&D activities hiring workers from R&D -intensive firms tend to perform better.[6]

More generally, the paper expands what is known empirically about knowledge transfer through plant-to-plant labor mobility (Fons-Rosen et al., 2017; Balsvik, 2011; Stoyanov and Zubanov, 2012; Parrotta and Pozzoli, 2012), and labor market-based knowledge spillovers.[7] In addition, our study adds to the literature on agglomeration advantages, recently reviewed by Combes and Gobillon (2015), and in particular on the microfoundations of such advantages based on learning.[8]

[3]A related body of work uses matched employer-employee datasets to explore network effects in the labor market. Dustmann et al. (2016) and Glitz (2017) document larger initial wage premium and longer job tenure for referred workers. Using the armed-force test, Hensvik and Skans (2016) report that firms workers with higher cognitive skills when hiring previous colleagues of current employees. Kramarz and Skans (2014) show that family ties are an important determinant for where young workers find their first job. Eliason et al. (2018a) assess the impact of social connections on the sorting of workers to firms.

[4]Burks et al. (2015) document that in call centers and trucking, referred workers yield substantially higher profits per worker than nonreferred ones, while Kramarz and Thesmar (2013) find that social networks strongly affect board composition in French public firms and are detrimental to corporate governance. Friebel et al. (2019) document that having an employee referral program reduces attrition and decreases firm labor costs.

[5]For instance Bloom et al. (2013) develop a methodology that allows to separate the impact of technology spillovers from the product market rivalry effects of R&D. They apply this approach to a 20-year panel of U.S. firms and shows that knowledge spillovers quantitatively dominate product market spillovers.

[6]In a similar vein Kaiser et al. (2015) show that the mobility of R&D personnel enhanced the patenting productivity of Danish firms during the period 1999-2004. Other papers combine register data with patents data and study features of the work history of inventors. See for instance Depalo and Di Addario (2014) and Kline et al. (2019)

[7]Serafinelli (2019) and Abebe et al. (2019).

[8]Rosenthal and Strange (2003),Moretti (2004),Kantor and Whalley (2014),Guiso et al. (2015), Ganguli

Another related body of work analyzes peer effects in the workplace induced by knowledge spillovers and finds mixed evidence. On one hand, for instance Waldinger (2010) finds that faculty quality is a very important determinant of PhD student outcomes. On the other hand, Cornelissen et al. (2016) find only small peer effects in wages in high skilled occupations.

Furthermore, our study is related to papers investigating network effects in science. For instance, Mohnen (2018) shows that network position is crucial in determining scientific production by facilitating access to other scientists' non-redundant knowledge through coauthorship links.[9] A final set of related studies focus on the mobility of immigrant scientists. For instance, Moser et al. (2014) focus on chemical inventions and compare the changes in US patenting by US inventors in research fields of German Jewish emigres with changes in US patenting by US inventors in fields of other German chemists. They provide evidence that the U.S. patenting activity has increased in the research fields of German-Jewish refugees after 1933.

2.2 Data and Descriptive Statistics

2.2.1 Overview

The data used in this paper covers Emilia-Romagna, Friuli-Venezia Giulia, Marche, Toscana, Trentino-Alto Adige, Veneto. A distinctive feature of this macro-region in northern-central Italy is the large presence of flexible producers frequently organized in districts.[10] Manufacturing firms in the districts of Third Italy specialize in metal, mechanic and electrical engineering, goldsmithing, plastics, furniture, ceramics, musical instruments, toys, fashion-wear.

Our data set covers the period 1987-2008 and pools two sources of information: the employer-employee matched data from the Italian Social Security Institute (Istituto Nazionale di Previdenza Sociale, INPS) and Patstat, the European Patent Office (EPO) Worldwide Patent Statistical Database.[11]

Information on local labor markets (*sistemi locali del lavoro*) is obtained from the National Institute of Statistics (ISTAT). The local labor markets (LLMs) are territorial groupings of municipalities characterized by a certain degree of working-day commuting by the resident population. In 1991 the municipalities or *comuni* in our 6 administrative

et al. (2020) and Tabellini and Serafinelli (2020). A related body of work studies the determinants of local innovation (Fons-Rosen et al., 2016; Huang et al., 2020)

[9] More generally, a number of studies explore co-author relationships (Jaravel et al., 2018; Azoulay et al., 2019; Zacchia, 2019).

[10] Several of such clusters feature some leading plants, especially in Veneto. See (Whitford, 2001) for a discussion.

[11] These two sources, combined for the period 1987-2006, are used in the study on inventors' returns to patents by Depalo and Di Addario (2014).

regions are grouped into 163 LLMs.

2.2.2 Administrative Records and Patent Data

INPS dataset follows all private-sector workers and firms over time. The available information at the individual level includes age, gender, municipality of residence and municipality of birth, work status (blue collar; white collar; manager; other), type of contract (full-time versus part-time) and gross yearly earnings. The information on plants includes: average gross yearly earnings, yearly number of employees, industry, plant location (at the municipality level), date of plant opening and closure.

From Patstat we obtain the universe of patent applications and grants presented at the EPO by any Italian "applicant" (i.e. the firm submitting a patent application and retaining the relative property rights). The database provides a detailed description of each patent submission, including its title, abstract and technological field, the name and address of all its inventors and applicants, the dates of application filing, publication and grant obtainment and the citations received.

Inventor status is defined based on the date of the first patent application. More precisely, we define a worker as being an inventor in year m if she is observed submitting a patent application in $t \leq m$.

Patstat does not have a plant identifier. Therefore a matching procedure was needed in order to merge the information to the INPS dataset (on the basis of the applicant name and location).[12] The resulting dataset includes the full work history of the inventors, i.e. Social Security info for all the plants at which an inventor has worked during her career, covering also plant-year observations before inventor's first patent application. For these plant-year observations we also observe the co-workers of the inventors.

2.2.3 Co-worker Network

We construct the plant's network using co-worker links, reconstructed from the employment history of each worker. More precisely, the employee's network comprises all former co-workers (employed in the same plant, other than the current one). The plant's network is a collection of co-worker networks of each incumbent employee.

The co-worker network is constructed for every plant in the sample for each year over the period of interest. In the first step, each year we distinguish incumbents as the workers who are employed in the first week of January. Next, for each incumbent we take

[12] The datasets were merged in several steps. We first attributed VAT codes to Patstat applicants on the basis of the name and location. We verified the code using four alternative datasets (Cebi, Infocamere, INPS, Orbis). Then INPS staff linked Patstat applicants to all possible INPS plants that had the same VAT identifier/same name and location (at the municipality level). Finally, INPS verified in its records that the inventors appearing in each patent submission were actually employed in the corresponding applicant (from Patstat).

Table 2.1: Characteristics of the sample of inventor hires (1992-2008)

	Connected	Displaced	Connected and Displaced
Share of inventor hires (%)	44.73	2.73	0.84

her employment history within past 5 years and build a network that comprises former co-workers.[13] Only plants where the number of workers is less than 500 are included in the sample. We exclude these very large plants, where the chances of establishing a link with every worker are low, to reduce the incidence of imprecise connections.

2.2.4 Plant Closures and Displaced Inventors

Our empirical strategy employs plant closures to identify the supply shock of knowledgeable workers within plant's own network. The INPS dataset includes the information on the date of plant closure; given the five year interval necessary to distinguish the plant's network, we are interested in closures between 1992 and 2008.

In order to identify "true" plant closures, i.e. the ones that are not a result of a merger, a change of tax identifier or a spin-off, we analyse worker flows from exiting plants and denote a closure as "true" whenever the maximum cluster of outflow from the closing plant to any other plant is below 50% of the workforce at the exiting one.[14] Only closing plants with more than 3 workers are subject to this procedure. The closures of plants with less than 4 employees are always classified as a "true" ones.

Using the information on plant closures, we are able to distinguish all employees who are subject to displacement, both inventors and non-inventors. We denote a worker as displaced if she loses the job in the year of plant closure. Inventors account for approximately 0.50% of all workers displaced due to plant closures in our data.[15]

2.2.5 Descriptives

Displacements and Connected Inventor Hires

Table 2.1 indicates that the percentage of connected inventor hires in our sample is almost 45 percent. This is larger than the share reported in other studies using a representative

[13]Only employment spells longer than 3 weeks are taken into account, whereas the spells of incumbents and former co-workers in past plants need to overlap by at least one week.

[14]Estimates are qualitatively similar if a 30% threshold is used

[15]The information on worker's contract end allows to perform additional checks of displaced employees. We select only those workers for whom the year of contract end and the plant closure coincide. Around 64% of displaced workers terminate their contract in the quarter preceding the closure. For the month and week preceding the closure the shares are respectively 51% and 45%.

Table 2.2: Summary statistics for estimation sample (1992-2008).

	Mean	SD	Min	Max
No. of Patent Applications	0.035	0.322	0	20
Citation-weighted Patent Count	0.034	0.756	0	56
Displaced Inventors $^{conn.}$	0.008	0.170	0	35
Displaced Non-Inventors $^{conn.}$	3.317	15.280	0	670
Inventor Hire $^{conn.}$	0.008	0.100	0	7
Inventor Hire $^{non-conn.}$	0.004	0.083	0	11
Employment Size	106.102	111.916	5	496
Plant Network	849.039	1180.871	1	22 197

Note: Sample size contains $80,310$ observations for $7,301$ plants. *No of Patent Citations* describes average sum of patent applications by the submission year. *Displaced Inventors*$^{conn.}$ is the number of connected inventors who are displaced in a given year, *Inventor Hire*$^{all.}$ is the number of all inventor hires, *Inventor Hire*$^{conn.}$ is the number of connected inventor hires, *Plant Network* is the number of former co-workers of current employees, as described in Section 2.2.3.

sample of workers and establishment (10-15 percent), pointing to stronger network effects for inventors than for the typical worker (see Figure B1 for the evolution over time in the share of connected inventor hires).

Estimation Sample

Our main sample consists of observations of plants that employ at least one inventor between 1992 and 2008. The outcome of interest is plants' innovative activity, therefore we take a patent application as a signal of the presence of some innovative output (Lotti et al., 2005). The panel includes $80,310$ observations for $7,301$ plants, and its main characteristics are summarized in Table 2.2.[16]

2.3 Econometric Framework

Our empirical analyses exploit plant closures for identification, in the spirit of Eliason et al. (2018a). The underlying idea is that plant p's ability to hire through the network is affected by displacements (at some other plant j) of inventors connected to p's current workers. We estimate (a) event-study models where the treatment is the displacement of a connected inventor and (b) IV specifications where we use the displacement of a connected inventor as instrument for the hire of a connected inventor.

[16] The average time between patent application and receiving a grant in our sample is 4.37 years.

2.3.1 Event-Study

We use an "event-study" research design as in Kline (2011) whose exposition we follow here. This design allows us to test for the presence of plants-specific pre-trends in innovation and to recover any dynamics of the effect of interest. Specifically, the regression equation is:

$$\begin{aligned}\ln(Y_{pilt}) = \beta_0 + \sum_{\tau} \beta_\tau D^{\tau}_{pt} + \beta_n N_{pt} + \beta_d Displaced_{ilt} + Trend_{it} + Trend_{lt} \\ + \lambda_p + \alpha_t + u_{pilt}\ ,\end{aligned} \tag{2.1}$$

where the dependent variable is the number of patent applications; p references plant, i industry, l local labor market (LLM) and t year. The D^{τ}_{pt} are a sequence of "event-time" dummies that equal one when the displacement of a connected inventor is τ years away. Formally:

$$D^{\tau}_{pt} \equiv I[t - e_p = \tau],$$

where $I[.]$ is an indicator function for the expression in brackets being true, and e_p is the year of the displacement. Therefore the β_τ coefficients characterize the time path of innovation relative to the date of the event.

We include year dummies (α_t), and allow for permanent differences across plants (λ_p), industry-specific and LLM-specific trends ($Trend_{it}$ and $Trend_{lt}$). We also control for controls for the the network size (N_{pt})

A potential identification concern arises if the directed shocks to the supply of knowledgeable labor also pick up market-level supply shocks or demand shocks. We do not expect this to be a major factor in our context. The sample comprises mostly closures of small to medium-size plants for which the market effects are likely to be small - the median closing plant has around 100 employees. To explore this possibility further, we control for displacements in the LLM x industry ($Displaced_{ilt}$).[17]

The results are obtained by estimating Equation (2.1) by OLS, adding a set of event-time dummies prior to and after the event, together with the controls. The event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. The event time indicator "+5" is set to 1 for all periods 5 periods after the event and 0 otherwise.[18] These endpoint coefficients give different weight to plants experiencing the treatment early or late in the sample period.[19] Therefore, in discussing the treatment effects, we concentrate on the event-time coefficients falling within $\tau = 0$ and $\tau = 3$ that are identified off of a nearly balanced panel of plants. We normalize β_{-1} to zero, so that all post-treatment coefficients can be thought of as treatment effects. We

[17]In Section B.1.1, we also perform a "placebo"-type analysis, exploiting the displacement of inventors with connections to plants in same LLM X industry.

[18]This constraint aids to diminish some of the collinearity between the year and event-time dummies.

[19]Notice that the sample of treated plants is unbalanced in event time.

cluster standard errors at LLM level.

2.3.2 IV Estimation

We consider 2SLS estimates where the displacement of a connected inventor is used as instrument for the hire of a connected inventor. This analysis assumes that the whole impact of the connected displacement of an inventor is mediated by a connected inventor hire. Specifically, denote with *Inventor Hire*$^{conn.}$ a dummy equal to one in the five years starting with the year of the hire of a connected inventor. The causal relation of interest is:

$$\ln(Y_{pilt}) = \beta_h \textit{Inventor Hire}^{conn.}{}_{pt} + \beta_n N_{pt} + \beta_d Displaced_{ilt} + Trend_{it} + Trend_{lt} + \lambda_p + \alpha_t + u_{pilt}. \tag{2.2}$$

We instrument *Inventor Hire*$^{conn.}$ with *Displ. Inventor*$^{conn.}$, i.e. a dummy equal to one in the five years starting with the year of the displacement of a connected inventor.

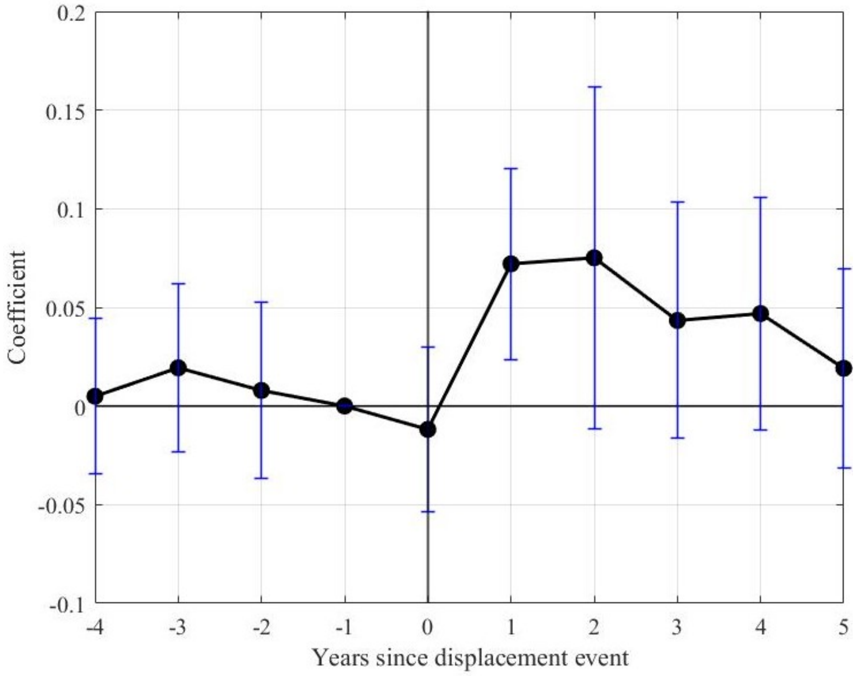
2.4 Evidence

2.4.1 Connected Inventor Displacements and Innovation: Event-Study Estimates

Figure 2.1 plots the baseline β_τ coefficients from estimating Equation (2.1), comparing changes in patent applications of plants that experience the displacement of a connected inventor both to plants that have not yet experienced such event and plants that will never do during our sample period. We distinguish 555 events over the period of interest. The Figure has two important features. First, there is no pretreatment trend in the coefficients, lending support to the validity of the research design. This support is reinforced by the lack of pre-trend in hires of inventors (connected or unconnected) documented in Figure 2.3 (discussed below). The second important feature of Figure 2.1 is that there is a upward shift in plant's innovation after the displacement of a connected inventor. In Figure 2.2 we drop the never treated plants, and therefore identification comes from the differential timing of treatment onset among the treated plants.

While the general pattern in Figure 2.1 and 2.2 is quite clear (and broadly similar), the individual β_τ coefficients are not estimated very precisely. We therefore offer more formal tests of the null hypothesis that the displacement of a connected inventor has no impact on plants' innovation. To increase statistical power we test hypotheses about the average of the β_τ coefficients over various time intervals (Table 1.5). The first row corresponds to Figure 2.1: the estimated average increase over the four years starting with the

Figure 2.1: Plants' Innovation, Relative to the Year of a Connected Inventor Displacement.



Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

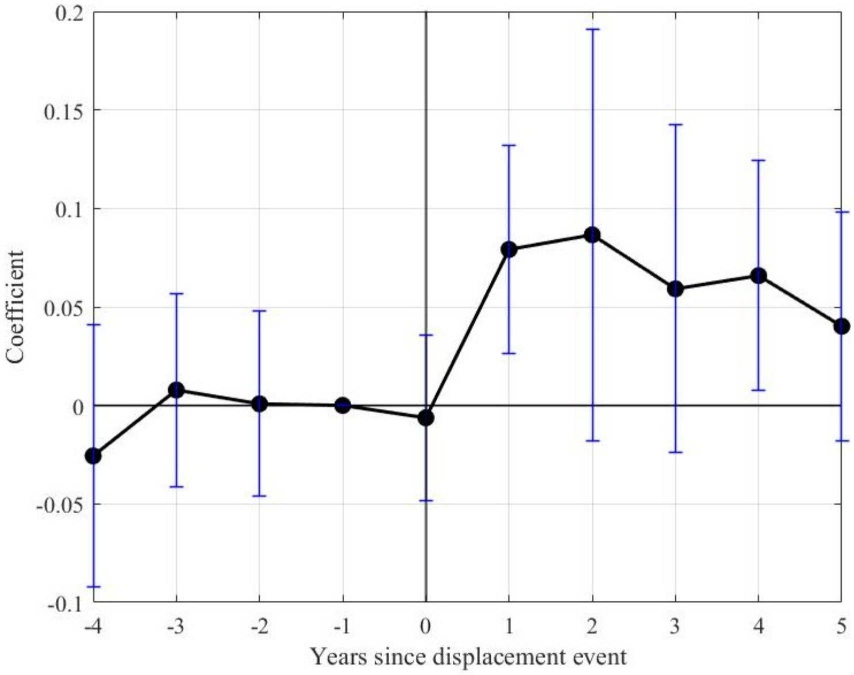
year of the event is 0.045 and statistically distinguishable from zero at conventional level. An increase in patent applications of 0.045 is equivalent to a 0.17-standard-deviation increase.[20] The second row of in Table 2.3 corresponds to Figure 2.1: the average increase is equivalent to 0.22 standard deviations.

2.4.2 Recruitments of Connected Inventors

How does the hiring of connected inventors evolve before and after displacements? To investigate this important aspect we estimate Equation (2.1) using as the dependent variable a dummy equal to one if a connected inventor is hired. Panel A of Figure 2.3 shows that the frequency of connected inventors hires has a clear top at the time of the displacement of a connected inventor. This is consistent with the hypothesis that plants take advantage of the displacement of a connected inventor to recruit connected knowledgeable labor. Panel B of Figure 2.3 shows that non-connected inventor hires do not exhibit any particular patterns with respect to the event of interest.

[20] The standard deviation in the sample of never treated plants is 0.26.

Figure 2.2: Plants' Innovation, Relative to the Year of a Connected Inventor Displacement. Treated Plants Only.



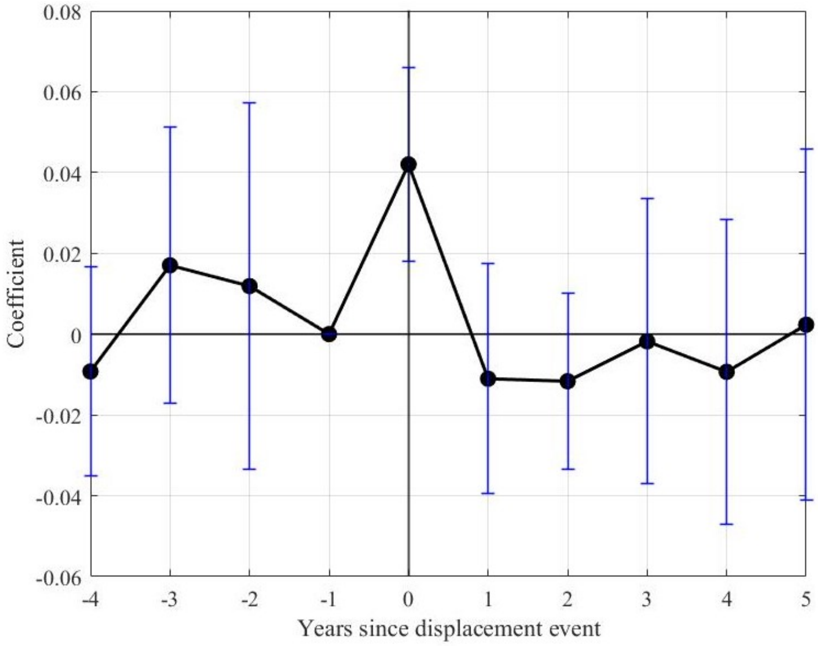
Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Table 2.3: Impact of Connected Inventor Displacements on Plants' Innovation - Event Study.

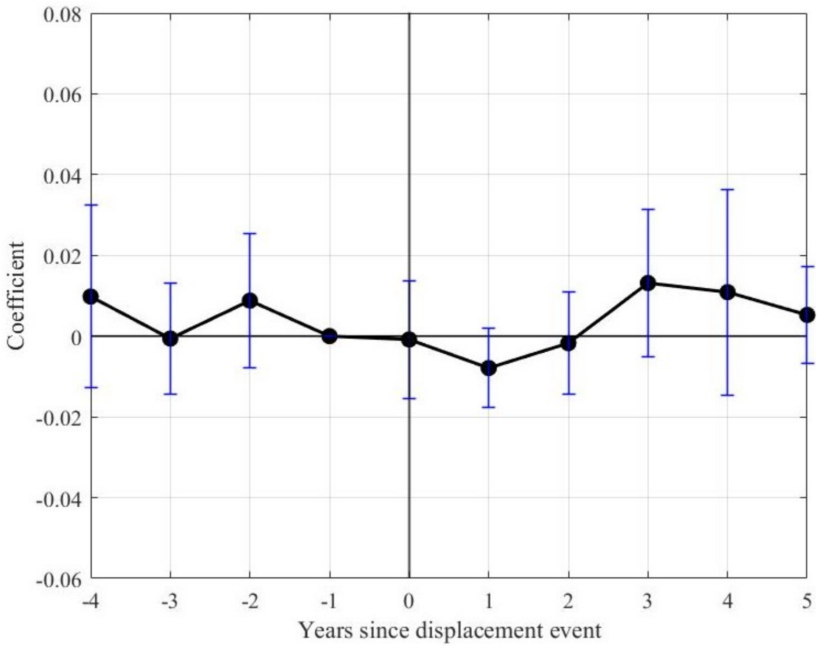
	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
Baseline Sample	-0.012	0.074***	0.045**	0.045**
	(0.021)	(0.029)	(0.020)	(0.019)
Treated Only	-0.006	0.083**	0.063**	0.057**
	(0.021)	(0.035)	(0.029)	(0.026)

Note: Estimates taken from specification of form given in Equation (2.1) where the dependent variable is the number of patents applications. The sample size for *Baseline Sample* is $80,310$ ($7,301$ plants), whereas for *Treated only* it is $6,954$ (551 plants). Sample includes only plants with more than 5 observations in the period of interest. The model includes year and plant fixed effects, industry trends and LLM trends, network size, number of displaced workers in the LLM$\times$industry$\times$year. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. $*p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Figure 2.3: The effect of network displacements on connected and market inventor hires - event study (1992-2008)



(a) Connected inventor hires



(b) Market inventor hires

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Table 2.4: IV Estimates of the Effect of Connected Inventor Hires on Innovation

Dependent Variable $No\ patent\ appl_t$	(1)	(2)	(3)
	Panel A: 2SLS Estimates		
Inventor Hire$^{conn.}$	0.478***	0.446***	0.502***
	(0.156)	(0.170)	(0.194)
F-stat, 1st *stage*	22.39	18.12	14.04
N	80,310	80,310	80,310
$Displaced_{ilt}$	-	+	+
Industry and Time Trends	-	-	+
	Panel B: First stage estimates		
Displ. Inventor$^{conn.}$	0.057***	0.053***	0.048***
	(0.012)	(0.012)	(0.013)
	Panel C: Reduced form estimates		
Displ. Inventor$^{conn.}$	0.027***	0.027***	0.024***
	(0.008)	(0.008)	(0.007)

NOTE: Estimates taken from specification of form given in Equation (2.2) where the dependent variable is the number of patents applications. Final sample includes only plants with more than 5 observations in the period of interest. Numbers in parentheses are standard errors clustered at the LLM level. Network size, plant and time fixed effects always included. $Displaced_{ilt}$: number of displaced workers in the same LLM×industry×year. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

2.4.3 Connected Inventor Hires and Innovation: IV Estimates

Table 2.4 displays the IV results. The coefficient on the dummy indicating the hire of a connected inventor is significant at 1 percent level. The effect is an increase in patents application of 0.5. To put the magnitude of the estimated effect in perspective, we calculate the fraction of overall variation in innovation explained by the hire of a connected inventor. A change of 0.5 is equivalent to a 1.56-standard-deviation increase.[21] The hire of a connected inventor is a major event for these plants, and we find this implied shift large but not unrealistic.

[21] The standard deviation in the estimation sample is 0.32. See Table 2.2.

Table 2.5: Citation-weighted Patent Counts, Poisson and Placebo Estimates

Panel A: **Placebo**				
Dep. Var.: *No Patent Applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
	0.006	0.009	-0.002	0.004
	(0.009)	(0.011)	(0.013)	(0.010)
Panel B: **Citation-Weighted Patent Counts**				
Dep. Var.: *No Patent Citations*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
	-0.055	0.174**	0.060	0.083*
	(0.045)	(0.090)	(0.100)	(0.043)
Panel C: **Poisson**				
Dep. Var.: *No Patent Applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
	-0.085	0.517**	0.389*	0.345*
	(0.201)	(0.233)	(0.202)	(0.188)

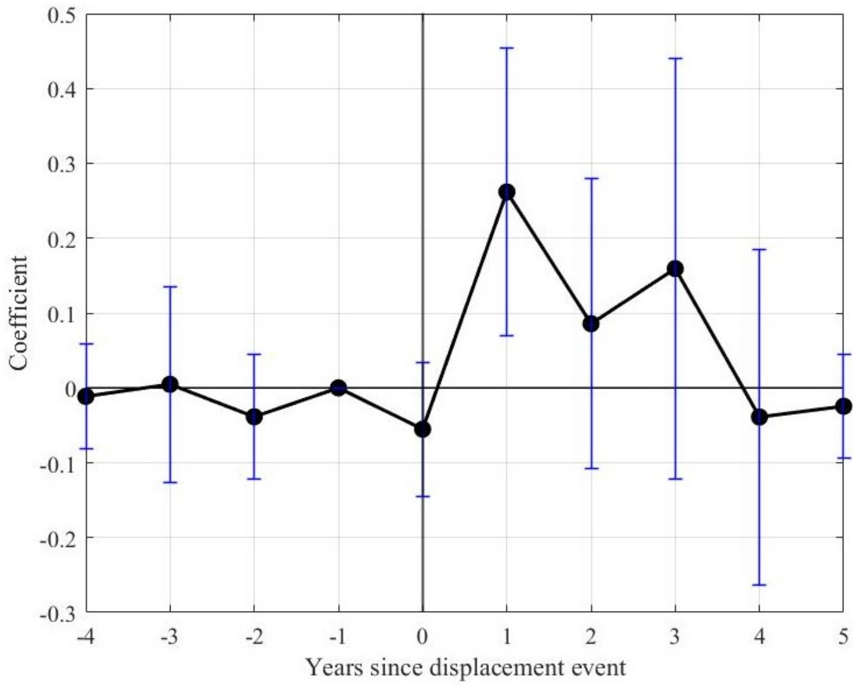
Note: Estimates taken from specification of form given in Equation (2.1). Panels A and C: the dependent variable is number of patent applications. Panel B: the dependent variable is Citation-Weighted Patent Count. The sample size is $49,176$ ($4,709$ plants) in Panel A, $80,310$ ($7,301$ plants) in Panel B and $9,486$ (707 plants) in Panel C. Sample in Panel C is smaller because plants with all zero outcomes are discarded in the estimation routine (Stata xtpoisson). The differences in sample size in placebo stem from the fact that more firms experience multiple placebo effect and hence were discarded from the sample. Final sample includes only plants with more than 5 observations. The model includes year and plant fixed effects, industry trends and LLM trends, network size, number of displaced workers in the LLM$\times$industry$\times$year. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

2.4.4 Validity and Robustness

Displacements with Connections to Plants in the same LLM x Industry (Placebo)

To further explore the possibility that the directed shocks to the supply of knowledgeable labor also pick up market-level supply shocks or demand shocks, we perform a ”placebo”-type analysis. Specifically we investigate the extent to which innovation at plant p reacts to displacement of inventors who are connected to other plants in the same LLM x industry but not p. The estimates, shown in Figure B2 and Table 2.5 indicate that the the estimated average change over the four years starting with the year of the placebo event is very small (an order of magnitude smaller than in the main estimates) and insignificant. These results suggest that the effect identified above is genuine to the improved capacity to

Figure 2.4: Citation-weighted Patent Counts, Relative to the Year of a Connected Inventor Displacement.



Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

employ connected inventors, and does not reflect market-level supply shocks or demand shocks.

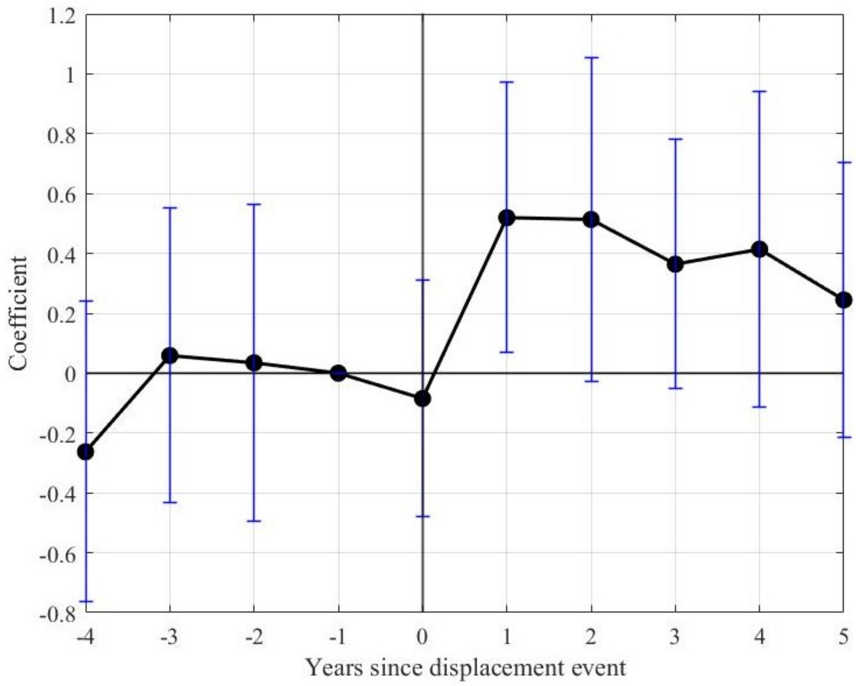
Citation-weighted Patent Counts

The baseline analysis uses simple patent counts. We explore the sensitivity of our results when we citation-weighted patent counts. In constructing this dependent variable, we employ the truncation correction weights devised by Hall et al. (2001) to correct for the fact that earlier patents will have more years during which they can receive citations. The estimates, shown in Figure 2.4 and Panel B of Table 2.5 are consistent with the main findings. Specifically the estimated average increase over the four years starting with the year of the event is statistically distinguishable from zero at 10 percent level and equivalent to a 0.13-standard-deviation increase.

Poisson Estimates

The estimation framework in Section 2.3.1 has several advantages. OLS is the best linear unbiased estimator and its consistency properties are transparent. Nevertheless, we

Figure 2.5: Plants' Innovation, Relative to the Year of a Connected Inventor Displacement, Poisson



Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

explore the robustness of our conclusion when using quasi-maximum likelihood fixed-effects Poisson estimates (QMLE Poisson), which address the count data characteristics of patents. The estimates, reported in Figure 2.5 and Panel B of Table 2.5, are consistent with the main findings. Specifically, the average increase over the four years starting with the year of the event is 41.2 percent.[22]

Event-study with linked, displaced inventor hires

The event-study in Section 2.4.1 is based on the displacement of a connected inventor. It is instructive to consider the event of the hire of a displaced connected inventor. The results are displayed in Figure B3 and Table B2: the estimated average increase over the five years starting with the year of the event is 0.28 and statistically distinguishable from zero at 10 percent level. An increase in patents application of 0.28 is equivalent to a 0.78-standard-deviation increase.[23]

[22]The percentage change is calculated as (exp(0.345)-1)*100=41.2.
[23]The standard deviation in the sample of never treated plants is 0.36.

2.5 Patent Increase Decomposition

Which workers are driving the increase in innovation after a hire of connected inventor, documented in Section 2.4.3? For instance, is the surge in innovation driven by cooperation between the connected inventor and the new colleagues? Or knowledge spillovers that poised the new coworkers of the hired inventor to increase patenting activity? Or peer effects? To explore these issues, we now turn to a decomposition of the patent increase.

2.5.1 Joiners and Experienced Employees

We define *Joiners*, as an inventors that joined a plant within five years prior to patent application. *Connected Joiner* is an inventor who entered to a plant no sooner than five years before the application and was a connected hire. All employees that didn't enter a plant within past five years are denoted as *Experienced Employees*. Note that *Experienced Employees* include both inventors and employees without any patent applications yet.

We further define two main groups of patent applications: i) Connected Joiners Applications and ii) Remaining Employees Applications. The first group includes all patent applications where at least one of the authors was a *Connected Joiner* in a plant of interest. Within this group we distinguish two subsets of patent applications, depending on the origin of the co-authors. If all of the co-authors of connected joiner are from the outside of a plant or the application is single-authored, we denote it as a *Single or Outside Co-Author* group. Otherwise, i.e. if the application is a collaboration of a connected joiner with co-workers in the new plant, we call it *Within Plant Co-Author*. The second major group of patents (Remaining Employees) comprises applications where none of the co-authors was a *Connected Joiner*. The remaining employees can be either *Experienced* ones or a *Non-Connected Joiners*. The three aforementioned groups provide clear distinction between the patenting activity brought by the connected hire, her collaboration with colleagues in a new plant and the activity of remaining employees at a new employer.

2.5.2 Results

Panel (b) of Figure B5 plots the share of all three considered patent categories over the period of interest. The share of *Connected Joiners*' collaboration outside of the plant and solo applications has decreased, whereas their joint patents with co-authors within a new plant remained on the same level. Similar patterns can be observed for the entire population of *Joiners* (Panel (a)) - decrease in collaboration outside of a plant and growing number of *Experienced Employees* applications. Note, however, that the latter effect might be propelled by the steady increase of inventor hires (Figure B1), and, as a consequence, inflow into *Experienced Employees* category.

Table 2.6: IV Estimates of the Effect of Connected Inventor Hires on Innovation

Patent Applications	**Connected Joiners** (single/outside co-author)	**Connected Joiners** (within co-author)	**Remaining Employees**
	Panel A: **2SLS Estimates**		
Inventor Hire$^{conn.}$	0.265**	0.217*	0.784**
	(0.121)	(0.124)	(0.402)
F-stat, 1st *stage*	15.21	15.21	15.21
N	80,310	80,310	80,310
Displaced$_{ilt}$	+	+	+
Industry and Time Trends	+	+	+
	Panel B: **First stage estimates**		
Displ. Inventor$^{conn.}$	0.049***	0.049***	0.049***
	(0.013)	(0.013)	(0.013)
	Panel C: **Reduced form estimates**		
Displ. Inventor$^{conn.}$	0.013**	0.011**	0.039**
	(0.006)	(0.005)	(0.016)

NOTE: Estimates taken from specification of form given in Equation (2.2) where the dependent variable is either of the three groups of patent applications displayed in the top row. Final sample includes only plants with more than 5 observations in the period of interest. Numbers in parentheses are standard errors clustered at the LLM level. Network size, number of hires, plant and time fixed effects always included. $Displaced_{ilt}$: number of displaced workers in the same LLM×industry×year. $*p < 0.1$, $**\ p < 0.05$,$***\ p < 0.01$.

In the decomposition exercise we use the econometric framework proposed by Equation 2.2 and the three aforementioned groups of patent applications as a dependent variable. The five year window in the definition of *Joiners* allows to distinguish the patenting activity of connected inventor hires, since the plants with multiple events are excluded from the estimation sample. The reference point for the results of decomposition presented in Table 2.6 are the findings of column (3) in Table 2.4.

Two main effects emerge from the decomposition analysis (Table 2.6): surge in the number of patents that *Joiners* pursue either alone or co-author with outside inventors, and an increase in patenting activity of the remaining employees. While the former is a signal of the knowledge and co-author network brought to the new plant by *Connected Joiner*, the latter indicates either a peer pressure or a transfer of knowledge caused by the entry of connected inventor. Interestingly, the effect of connected inventor hire on her collaboration with new co-workers (*Within Plant Author*) is relatively weak.

The event study analysis of patent count decomposition (Table B3) brings additional insight on the dynamics of the increase in plants' innovative activity and potential channels of knowledge diffusion. The increase in *Connected Joiners*' single and outside plant co-author applications is the strongest right after the displacement event and fades in the later years. The impact on the applications of Remaining Employees appears the strongest in the long run.

2.6 Concluding Remarks and Future Work

The central empirical goal of the paper is to measure the extent to which access to connected knowledgeable workers impacts plants' innovation. Our identification strategy exploits the shocks that displacements of inventors generate to the connected supply of knowledgeable labor of plants with employees that are former coworkers of the displaced. Estimates from event-study and IV models indicate that the improved capacity to employ connected inventors increases plants' patenting activity. In the future, we plan to provide further evidence on extent and nature of knowledge diffusion through the network, since we have just scratched the surface in this regard. For instance, using info on citations in the patents data, we plan to study whether the hiring plants are more likely to build on the knowledge of previous colleagues of connected displaced inventors.

Chapter 3

Job Automation and Worker Reallocation

3.1 Introduction

Job automation is most commonly defined as the process in which a particular set of tasks within an occupation can be performed by industrial or service robots. The current pace of implementation of industrial robots is unprecedented and poised to accelerate in the upcoming decade, as installation costs are expected to drop in some industries by 22%, leaving around 47% of US employment in danger of automation.[1] Acemoglu and Restrepo (2017a) (hereafter AR) report that the increase in industrial robot usage has a significant impact on local labor markets and claim that the automation is a labor-displacing force. They find that one more robot in a commuting zone reduces employment by 6.2 workers and decreases average wage by 0.73%.[2] While most of the existing works document the labor-displacing effect of automation, we know suprisingly little on whether (and how) it affects displaced workers. Empirical analysis of AR suggests that workers hit by automation are more likely to stay out of labor force. A recent study of Bessen et al. (2019) also finds that automation increases separation probability, leading to longer non-employment spells of workers displaced by the robots.

The main purpose of this paper is to study the effects of job automation on workers' occupational mobility. The contribution of the work is twofold: first, I uncover novel

[1] Formally job automation is defined as workers being replaced by *"automatically controlled, reprogrammable, multipurpose machines that do not need human operator"* (International Federation of Robotics definition). The largest purchasers of industrial robots are China, South Korea, Japan, United States and Germany, representing 73% of robot sales volume in 2016. For further details and statistics on industrial and service robots see IFR World Robotics reports https://ifr.org/downloads/press/Executive_Summary_WR_2017_Industrial_Robots.pdf. The estimates are based on Boston et al. (2015) report and Frey and Osborne (2017).

[2] Compared to commuting zone with no exposure to robot. They name this the displacement effect. It is countered by productivity gains of firms that implement robots, which can lead to employment gains. AR find that the former effect dominates.

empirical regularities regarding characteristics of occupations that are at risk of automation and mobility patterns of displaced workers. Second, I build a search and matching model with technological acceleration, human capital accumulation and skill transferability to understand how much of the observed differences in occupational mobility can be explained by job automation. The model can be used to evaluate policies that offset the wage loss caused by automation and incentivise workers at risk of it to search more actively while non-employed.

In the empirical part of the paper I develop a measure of occupational-level exposure to job automation with the use of industry level data on the stock of robots and distribution of employment across industries within each occupation. Those ranked above 66th percentile of the exposure index (denoted interchangeably as jobs with high exposure or high risk of automation) are manual task-intensive, manufacturing jobs such as machine operators, assemblers, etc.[3] They have on average lower training requirements and employ individuals with lower educational attainment levels than the jobs with lower risk of automation.[4] Then, using the panel of individual employment histories from Survey of Income and Program Participation (SIPP), I show that job automation is an important factor driving occupational mobility decisions of displaced workers, along with learning about own abilities and business cycle.[5] Three key findings emerge from the analysis.

First, I uncover the composition effect of fairly stable occupational mobility rates documented over the past two decades: significant increase in mobility of high exposure occupations was offset by the decline among low-risk occupations. Non-employed workers with high exposure to automation have on average 10 percentage points higher probability of changing broad occupational category (1-digit occupational classification) than their counterparts with low risk. The results hold for every level of occupational classification. Prior to implementation of the first industrial robots (early 90s), occupations did not differ significantly in mobility levels depending on their exposure to automation. Second, the mobility of exposed workers is not U-shaped: mainly low earners within occupations at risk of automation tend to reallocate. Third, conditional on occupational mobility, exposed workers face significantly lower probability of moving into jobs with higher average wage. Only those above 90th percentile of wage distribution within prior occupation tend to switch into jobs with higher average wage and higher cognitive skill intensity. As a result, earnings of workers employed prior to displacement in occupation with high exposure recover slower than of their counterparts with low risk.

[3]These results are, however, somewhat mechanical given the data used in the study. To the best of my knowledge, the only available dataset on the usage of robots contains information on the stock of industrial robots, leaving service ones undocumented. Bessen et al. (2019) document however, that the job automation has the largest effect on manufacturing, what may justify the focus on industrial robots.

[4]Training requirements is an index $\in (0, 1)$, based on O*NET Job Zone measure of how much preparation (e.g. education, on-the-job training, etc.) each occupation requires.

[5]For more on the key factors driving occupational mobility see e.g. Kambourov and Manovskii (2008), Papageorgiou (2014) or Groes et al. (2015).

The second contribution of the paper is to offer a theoretical framework that studies the mobility patterns caused by job automation at the presence of labor market frictions. Based on the empirical findings, I develop an equilibrium search and matching model with technological acceleration, human capital accumulation and segmented labor markets. It builds on the technological obsolescence literature (e.g. Violante (2002), Postel-Vinay (2002) and Michelacci and Lopez-Salido (2007)), where acceleration in equipment technology increases productivity differentials across machines. In this framework workers are matched with jobs that represent certain technology or machines that age with tenure. The key feature of the model is technological distance between two machines of different tenure, defined by the speed of technical change. The island structure of the model allows for the reallocation of unemployed workers across occupations, depending on their human capital and skill transferability. The latter is a key mechanism of mobility decision that determines the loss of human capital once reallocating between different occupations. More precisely, it is designed as the probability that unemployed workers will start with lower human capital level in the new occupation. The probability of human capital loss depends on the proximity between two occupations. Unemployed workers face a trade-off between costly reallocation and job search in a slack labor market. In order to account for other factors behind occupational mobility, the model also allows for the exogenous reallocation of unemployed workers.

In the calibration exercise, I measure the technological speed (or speed of labor-displacing technology) as the change in stock of robots in particular occupations. The underlying assumption is that occupations with high risk of automation are the ones with larger technological distance between matches with different job tenure. In other words, matches in occupations with high risk of automation become technologically obsolete faster than in other jobs, what may lead to match destruction. The calibration of the model matches salient features of the economy and generates three facts documented in the empirical part of the paper. In the initial steady state calibrated to the 1996 US economy, the endogenous reallocation decisions account for around one fifth of all mobility. The response of the economy to an automation shock follows the patterns observed in the data: increase of mobility and wage loss of workers at risk of automation with magnitudes similar to changes between 1996 and 2012. The occupational mobility gap increases by 37%, what accounts for 79% of the total surge. Due to the increase in mobility and skill transferability mechanism rooted in the reallocation decision, the average level of human capital depreciates. This in turn leads to output loss, as human capital is not fully transferable between two occupations and exposed workers start switching to more distant occupations. To address this issue I propose policy counterfactuals that aim at providing off-the-job training to unemployed workers at risk of automation. A training that corresponds to one year of education in new occupation will reduce the loss of output by nearly 20%.

This work is most closely related to papers by Acemoglu and Restrepo (2017b,a, 2018d,b,c,a) who study the impact of job automation on US local labor markets. The effects of technological change on labor demand in Europe were described by Gregory et al. (2019), who document that the routinization led to positive net labor demand in 27 European coutries between 1990 and 2010. Graetz and Michaels (2018) report that industrial robots increased labor productivity and value added. Opposed to most of the papers on automation that use the *International Federation of Robotics* (hereafter IFR) data on the stock of industrial robots, Green Leigh and Kraft (2018) develop a novel proxy for automation - density of robot installers in metropolitan areas. The alternative measure of exposure to robots introduced in Section 3.2.1 is based on the work of Frey and Osborne (2017) who, using machine learning, classify each occupation according to how susceptible it is to automation. In their recent paper Bessen et al. (2019), employing Dutch administrative records and balance sheet data on costs of automation, find that in fact, increase in automation at the firm level leads to surge in separation probability, lengthens the non-emplyment periods of displaced workers and generates wage loss that amounts to 11% of annual earnings over the 5 years following the automation event. Not surprisingly, workers displaced by automation shock are more likely to retire earlier and receive welfare payments, however, only 13% of wage loss is offset by unemployment benefits. The impact of industrial robots in the decades to come is the focus of e.g. Brynjolfsson and McAfee (2014), Ford (2015) or Boston et al. (2015). Growing number of works distinguishes automation and demographic changes as the trends that may have a profound macroeconomic consequences over the next decades (see e.g. Acemoglu and Restrepo (2018a), Basso and Jimeno (2020), Jimeno (2019)) The number of papers that study the worker, rather than aggregate effects of technological progress, is rather limited, with notable exception of Battisti et al. (2017) who study retraining among workers subject to routinization.

The importance of occupation specific human capital for reallocation decisions was raised by Kambourov and Manovskii (2009). Learning about own abilities as a key driving force of occupational mobility was studied previously by Papageorgiou (2014) with the use of a matching model. Groes et al. (2015) document the U-shape of occupational mobility and the direction of the switch using Danish administrative records. Carrillo-Tudela and Visschers (2020) stress the role of business cycle in mobility decisions: during economic downturn displaced workers find it less profitable to switch their occupation. As a result, the unemployment spell lengthens and job finding rate decreases. The role of worker heterogeneity across labor markets was documented empirically by Barnichon and Figura (2013). Wiczer (2015) and Carrillo-Tudela and Visschers (2020) develop job search models to study the impact of aggregate productivity, occupation-wide shocks and cyclicality on workers' mobility decisions. The theoretical framework in this paper builds on the technological obsolescence models developed by the job search literature: Violante

(2002), Postel-Vinay (2002) and Michelacci and Lopez-Salido (2007).

The paper proceeds as follows: Section 3.2 provides a description of the data, design of the measure of exposure to automation and statistics of the final sample. Section 3.3 presents novel empirical findings, followed by theoretical framework outlined in Section 3.4. Quantitative analysis and policy implications are described respectively in Section 3.5 and 3.6, whereas Section 3.7 concludes. All additional findings, materials and robustness checks that are not the main focus of the paper are documented in the Appendix.

3.2 Data

The empirical findings of this paper can be replicated using various datasets that allow to study employment decisions of displaced workers (e.g. linked CPS, ASEC, etc.). The empirical analysis employs only one selected database, leaving the results from alternative sources to the Appendix. I have chosen Survey of Income and Program Participation (SIPP) as the most comprehensive and widely used source of information on occupational mobility and employment history.

3.2.1 Automation

Job automation is most commonly defined as a replacement of particular task or set of tasks within a job by industrial robots. One of the major obstacles in the literature is a measure of industrial robot implementation on individual or firm level. Some works (e.g. AR) define the exposure to robots for each Commuting Zone based on industry-level data of International Federation of Robotics. Others like Green Leigh and Kraft (2018) use the concentration of industrial robot installers as a proxy for geographical intensity of automation.[6] Only recently Bessen et al. (2019) use administrative records on automation costs on the firm level to identify the automation shock. In this work I introduce three measures of exposure to automation on the occupational level. The baseline index follows the strategy similar to AR in order to distinguish a risk of automation for each occupation defined as in Census occupational classification. The first alternative measure is based on the work of Frey and Osborne (2017), whereas the second explores the information of major applications of industrial robots and the detailed description of occupational tasks.

[6]although Green Leigh and Kraft (2018) are able do distinguish number of installers for particular metropolitan areas, their analysis does not cover the whole US territory. Moreover it does not allow to study exposure on industry or occupational level.

Baseline Measure

The baseline measure of exposure to automation of each occupation is based on the IFR (*International Federation of Robotics*) data - stock of industrial robots by year, country and industry, based on annual surveys of robot suppliers. The data is available for 50 countries over the years 1993 - 2017, however the information on robots prior to 2000s is avaliable only for a small subset of them.[7] The records on stock of robots in the US start in 2004. IFR reports the stock of robots in 7 broad industry categories (agriculture, forestry and fishing; mining and quarrying; manufacturing; utilities; construction; education, research and development; other non-manufacturing). Within manufacturing it distinguishes more detailed categories: food and beverages, textiles, wood and furniture, paper, plastic and chemicals, glass and ceramics, basic metals, metal products, industrial machinery, metal unspecified, electrical and electronics, automotive, other vehicles, other manufacturing. To construct the measure of robots per thousand of workers I use the annual employment counts for each of the aforementioned industries in the countries of interest provided by EU KLEMS (Jäger (2017)) database. The strategy of computing the measure follows closely AR, statistics for each industry between 1993 and 2017 are provided in the Appendix C.1.1.

The baseline measure of exposure to automation uses the stock of robots in 9 European countries to first, account for the change in stock between 1993 and 2004, and second to use it as exogenous exposure to robots.[8] More precisely, the exposure of occupation $o = 1, 2, ..., O$ to industrial robots between t and $t + \tau$ is defined as:

$$Exposure_{o,t,t+\tau} = \sum_{i \in \mathcal{I}} l_{io}^{1990} \Big(p_{30} \big(\frac{R_{i,t+\tau}}{L_{i,1990}} \big) - p_{30} \big(\frac{R_{i,t}}{L_{i,1990}} \big) \Big) \tag{3.1}$$

where l_{io}^{1990} is the employment share of industry i in occupation o in 1990 Census and $p_{30}(\cdot)$ is the 30th percentile of robots per thousand of workers among nine European countries. AR use 1970 Census to distinguish employment shares, however the occupational categories change every decade and necessity of using crosswalks makes 1990 shares more appealing. Occupations are distinguished following Census 1990 3-digit classification. Table 3.1 clusters occupations into one of 13 main Census 1990 occupation categories. Not surprisingly, the occupation categories that have the highest exposure to automation are low-skill production occupations such as machine operators, assemblers, precision production, material movers, handlers, etc. Interestingly, five categories with the highest exposure to robots account for approximately one third of labor force (31.7% of employment as of 1990, intensive margin). It corresponds to findings of Frey

[7] Those are 9 European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden and United Kingdom.

[8] Note that construction of the baseline exposure measure is the only time I use the data from European countries. All remaining analysis focuses solely on the US.

Table 3.1: Robot adoption by occupational group, 1993 - 2016.

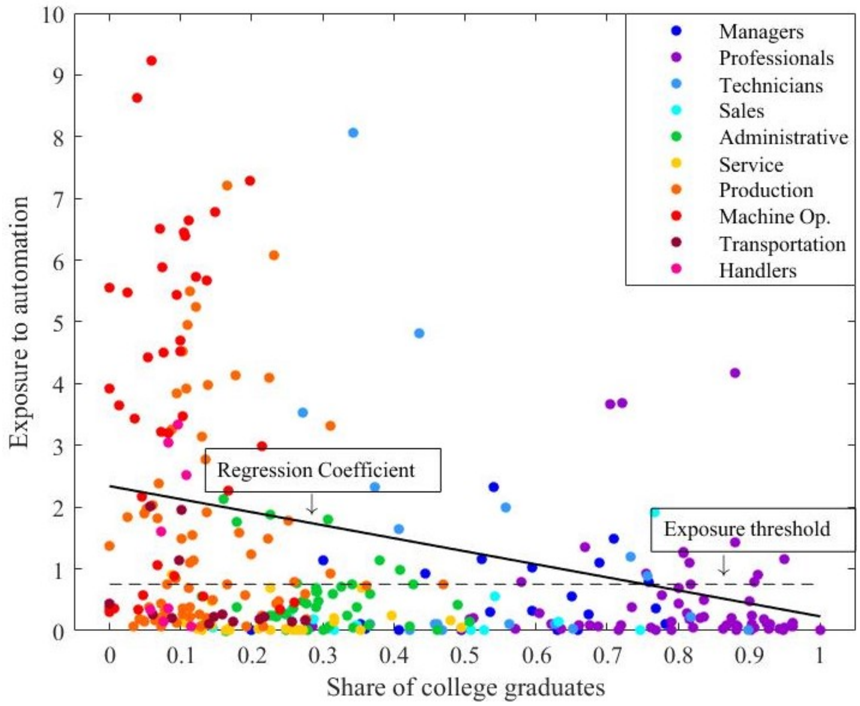
	Employment share1990	EXPOSURE TO ROBOTS 1993-2000	1993-2007	1993-2012	1993-2016
Executive Admin, Managerial	13.87	0.181	0.631	0.793	0.904
Professional Speciality	13.53	0.112	0.387	0.469	0.519
Technicians and Related Support	**3.72**	**0.203**	**0.783**	**0.933**	**1.018**
Sales	11.03	0.049	0.172	0.216	0.248
Admin. Support, incl Clerical	14.70	0.140	0.480	0.604	0.697
Private Household	0.59	0.005	0.021	0.029	0.036
Protective Services	1.85	0.049	0.180	0.229	0.266
Service, except Protective - HH	7.91	0.043	0.145	0.189	0.226
Farm, Forestry and Fishing	2.94	0.064	0.165	0.210	0.246
Precision Production, Craft, Repair	**12.33**	**0.353**	**1.293**	**1.714**	**2.027**
Machine Operators, Assemblers, Insp	**7.59**	**0.862**	**3.102**	**4.035**	**4.709**
Transportation and Material Moving	**4.55**	**0.198**	**0.712**	**0.946**	**1.137**
Handlers, Equip, Cleaners, Helpers, Lab	**3.46**	**0.299**	**1.041**	**1.378**	**1.630**

NOTE: All occupational groups are distinguished following the Census 1990 1-digit occupational classification (broad occupational categories). Employment shares are computed from 1990 Census sample.

and Osborne (2017), who claim that nearly 50% of US employment is susceptible to automation. Throughout the paper I use the notion of high and low exposure to automation. High exposure of occupation o is denoted when its value of the index defined by 3.1 is among top 33 percentile of exposure distribution, whereas low exposure means that is it in bottom 33 percentile.

Figure 3.1 illustrates the relationship between the share of college graduates and exposure to automation for all considered occupations and clusters them into broad occupational categories. The relationship between the share of college graduares employed within occupation and exposure to automation is negative. Individuals employed in occupations with high risk of automation have on average lower education attainment than all remaining groups. One of the shortcomings of proposed measure of exposure is the fact that is doesn't take into account task-specificity of each occupation. As a result, some jobs with high skill requirements employed largely in manufacturing (e.g. technicians or engineers) are among most susceptible to automation. To illustrate the issue, Table C2 lists 10 occupations with highest and lowest exposure index. In all specifications chemical engineers are among occupations with the highest exposure to automation, as they are employed in industries with highest usage of robots (plastic and chemical products, basic metals, etc.). I correct that by examining only occupations with high manual task intensity. The index of manual task intensity is constructed from the O*NET database

Figure 3.1: Exposure to automation and share of college graduates by occupation categories, IFR and SIPP 1993-2016.



and follows standard principal component analysis widely used in the literature.[9] I denote occupation as manual if it's index of manual task intensity is above the median. The baseline measure assigns high exposure to automation to high-skill jobs such as executives, managers, clerks and other professional specialities, whereas the measure with manual task-intensity corrects for that (Appendix C.1.1) and attributes high risk to manual tasks intensive occupations (e.g. machine operators, assemblers, etc.). Full exposure by occupational category with manual task intensity correction is presented by Table C3.

Alternative Measures

Two alternative measures are distinguished to check the consistency of the baseline index and use the richness of IFR database. First alternative measure employs the detailed description of robot application provided in the IFR robot data, whereas the latter uses the work of Frey and Osborne (2017) who classify each occupation according to how susceptible it is to automation. The IFR data provides description of robot application that can be classified into five main categories: handling operations, welding and soldering, dispensing, processing and assembling. Within those broad categories there are 33 descriptors of particular task performed by a robot (e.g. palletizing, arc welding, laser cutting, etc.). The application categories are then matched with occupational task descriptors documented in

[9]Manual tasks are distinguished following Autor et al. (2003).

the first edition of O*NET database (1998 issue).[10] It distinguishes around 12,000 task descriptions, with average of 10 tasks per occupation. Detailed information on matching procedure is provided in Appendix C.1.2. Having identified the tasks within each occupation (3-digit classification) that can be commissioned to industrial robots, I develop two measures of exposure to automation that look at i) share of tasks that can be automated and ii) share of tasks weighted by the change in exposure of each application. In some occupations the share of tasks that can get automated reaches 75%, what suggests the main difference between routinization and automation - the scope of task replacement. Main occupational categories at risk of automation overlap with the baseline measure - machine operators and production workers. Task-based measure delivers similar findings on occupational mobility as the baseline one. Results are presented in Appendix C.1.2.

Second alternative measure is based on the work of Frey and Osborne (2017) who measure susceptibility of each occupation to job automation. They distinguish major bottlenecks for automation and identify them for each occupation with the help of task intensity measures from O*NET occupational database.[11] Using Gaussian process and machine learning each SOC occupation has assigned probability of being computerized. Authors argue that occupations with probability higher than 70% are likely to be automated. Such approach might be criticized as too simplistic and not fully capturing the complex nature of automation and artificial intelligence, it has however certain advantages useful for my analysis. First of all the probability of being automated is set once, as of the technological progress in 2017. By identifying the bottlenecks for computerization it is forward-looking, what may be a threat to the analysis that goes back to 1990s. Within the set of occupations marked as highly automatable, the majority consists of machine operators, manual labour and cashiers, jobs that since 2000s are subject to intensified automation. Moreover, the measure of Frey and Osborne (2017) captures occupations for which the demand decreased not only due to implementation of industrial robots but also growing digitalization, such as payroll clerks, data entry keyers or insurance underwriters. Another interesting feature of proposed approach is that it's not only constrained to particular manufacturing industries. IFR reports show that in recent years we can observe intensified usage of robots in industries other than manufacturing, such as services.

Following Frey and Osborne (2017), I classify each of SOC occupations as highly

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[10]The reason for using the earliest issue of O*NET is motivated by the fact that I want to distinguish tasks within occupation that later on were subject to automation. Next steps of the project assume distinguishing task measure using fourth edition of *Dictionary of Occupational Titles* (DOT).

[11]More precisely they define three major bottlenecks inhibiting engineering from computerization: *perception and manipulation* (PM), *creative intelligence* (CI) and *social intelligence* (SI) tasks. The first group of tasks refers to working in difficult conditions, unstructured work conditions, handling irregular objects, etc.; the creative intelligence comprises set of tasks such as creating ideas, artistic creativity, etc.; social intelligence is a wide range of skills usually requiring negotiation, persuasion and care. Each of the bottlenecks is identified in the O*NET database under following task variables: finger and manual dexterity, cramped work space, awkward positions (for PM), originality and fine arts (for CI), social perceptiveness, negotiation, persuasion, assisting and caring for others (for SI).

Table 3.2: Exposure to robots, training requirements and education, SIPP 1996-2013

	Training Requirements		**% of Higher Education**		**% of High School Graduates**	
	Baseline	Manual	Baseline	Manual	Baseline	Manual
High Exposure	0.49	0.47	25.96	20.73	84.03	82.60
Middle Exposure	0.50	0.51	29.32	31.42	89.93	88.67
Low Exposure	0.59	0.59	29.08	32.23	83.20	84.99

NOTE: First two columns present training requirements using occupation data. Each occupation (one of 384) has attributed value of training requirement index and is weighted by its employment share. Training requirement index is taken from O*NET Job Zone index (1-5) and scaled between 0 and 1. It describes how much preparation (education, job training, etc.) each occ. requires. Remaining columns present education attainment from the final sample.

exposed to automation if the probability of being automated exceeds 70%. To validate this measure I perform number of comparisons and replicate empirical findings of AR, all of which are presented in Appendix C.1. Indeed, the results with the new measure of exposure to automation are close to Acemoglu and Restrepo (2017a). The key issue that needs to be addressed is the relationship between exposure to automation and routinness of occupations. One of the most important questions in the literature of job automation is whether those are two different phenomena. It is not however the aim of the paper to take clear stand in this discussion. The data suggests that the major difference consists in the skill distribution of each measure. Literature on skill-biased technological change identifies routine tasks in the middle of skill distribution. The statistics provided by Appendix C.1 show that the alternative measure follows the baseline index. Occupations with high exposure to automation are concentrated not only in the middle but also among low skilled occupations.

3.2.2 Displaced Workers

The final sample of workers experiencing non-employment period is distinguished using panels 1996 - 2008 of Survey of Income and Program Participation (SIPP). The reason for omitting panels prior to 1996 is the change of methodology of denoting the current employer and employer change in 1996 panel, that could affect the distinction of job transitions. SIPP provides the panels of nationally-representative sample of US inhabitants tracked over the period of 4 years. It has an advantage over other datasets in two key aspects: i) it is a reliable and widely used source of information on occupational mobility of workers that ii) follows them in case of domestic migration.[12] Constructing the sample I first distinguish workers that experience non-employment spell and then aggregate into

[12]See Carrillo-Tudela and Visschers (2020) for occupation mobility and Kaplan and Schulhofer-Wohl (2018), Molloy et al. (2014) for interstate migration.

quarterly data. For more details on either stage see Appendix C.2.

The final sample includes private sector workers aged 25-60, who experienced period of non-employment that lasted more than 3 weeks.[13] It contains 24,601 job transitions that involved period of non-employment. Alternative strategies of measuring occupational mobility using SIPP (e.g. Carrillo-Tudela and Visschers (2020)) yield similar results (see Appendix C.2). The findings on occupational mobility from the baseline sample are confronted with alternative samples constructed from linked Current Population Survey (CPS) and Annual Social and Economic supplement (ASEC) to CPS data. Both of the alternative samples are constructed using fairly similar strategy: contain job transitions of private sector workers aged 25-60 between 1995 and 2018.[14] The major drawback of linked CPS is it's limited panel structure - individuals are followed twice in 4 consecutive months with 8 month break between the interviews. As a result, it does not capture the long-term unemployed workers or unemployment spells within 8 months between the interviews. Results of linked CPS and ASEC are presented in the Appendix.

3.2.3 Sample Statistics

Occupations exposed to automation are typically manual task intensive (machine operators, assemblers, etc.) and require lower educational attainment. Table 3.2 displays the training requirement and education level in occupations with high, middle and low exposure to automation. Training requirements are based on O*NET database Job Zone index and indicate (on the scale 0 to 1) how much preparation (education, job training, etc.) each occupation requires. Jobs with high exposure to automation have significantly lower training requirements compared with any other category. Similarly for education: only around one fifth of workers employed in occupations with high exposure to automation have college degree, whereas for the remaining categories the percentage is around one third. Basic characteristics of the restricted sample are provided by Table 3.3. The mean unemployment spells are longer than in the literature since the sample includes only spells of more than 3 weeks. By including job-to-job transitions the average unemployment spell drops to 12.1 weeks. The mobility patterns in the final sample follow the stylized facts of the literature: higher occupational mobility for young and college educated workers.[15] The share of workers with high exposure to automation declines slightly between 1996 and 2012.

[13] By non-employment period I denote both unemployment and staying out of labor force. Job transitions taken into account are E-U-E, E-$\cancel{E}$-E and their variations.

[14] Prior to 1995 CPS does not include information on the change of employer. The size of final sample is $107,056$. CPS does not follow individuals in case on migration and hence cannot be used to study geographical mobility of displaced workers.

[15] Note that the higher occupational mobility of young workers (aged 25-35) corresponds to one of the driving forces of the mobility: learning about own abilities. Young workers have a noisy signal on their own skills, as it updates with tenure, they may decide to change the current occupation.

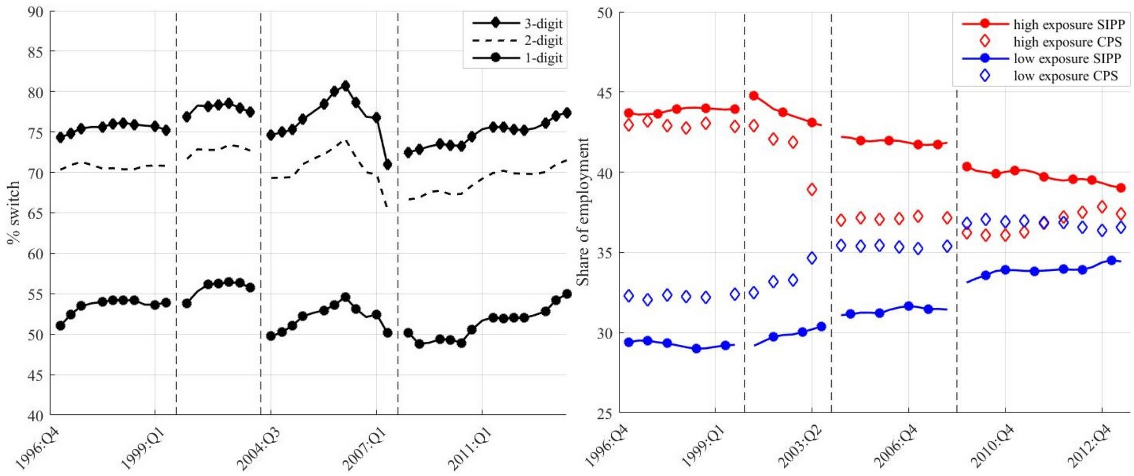
Table 3.3: Sample statistics, SIPP 1996 - 2013

	All	**PANEL**			
		1996	2001	2004	2008
Occupation mobility (1-digit)	53.05	53.57	54.51	52.17	52.57
Young	55.69	56.27	58.02	53.00	56.04
Prime Age	50.78	50.89	51.75	51.45	49.73
Male	54.20	53.49	53.96	54.30	54.68
Female	51.93	53.64	55.04	50.06	50.21
High School	51.66	52.90	52.60	51.07	50.31
College	54.14	54.29	56.28	52.91	53.98
Share of exposed to automation (%)	37.13	36.96	36.73	38.17	36.73
Unempl. duration (mean, weeks)	25.65	23.61	21.93	22.17	31.48
High exposure	24.40	20.73	20.38	20.74	31.79
Low exposure	26.95	26.03	23.53	24.18	31.08
N	24,601	6,732	3,852	5,891	8,126

NOTE: The sample includes non-employed individuals aged 25 - 60 working in a private sector. All non-employment spells shorter than 4 weeks were excluded. Age category 'Young' contains individuals with no more than 35 years old, whereas category 'Prime' includes workers between 35 and 60 y.o. Demographic group 'High School' represents those with high school diploma or less, 'College' individuals hold at least college degree or have some college experience. All individuals are weighted by respective SIPP weights.

Second part of Table 3.3 sheds more light on the unemployment spell of workers exposed to automation. Initially they experience significantly lower non-employment spells, however, in panel 2008 the difference has vanished. Between 1996 and 2008 panels, the non-employment spell of workers exposed to automation increased by nearly 3 months, compared to 1.5 month for the remaining non-employed individuals. Naturally, some part of the increase may be caused by the Great Recession. The aggregate occupation mobility reveals moderate downward trend prior and rebounce after the Great Recession. Figure 3.2 presents quarterly rate of occupational mobility (moving average) for all Census 1990 classification digit levels. The panel structure of the data is clearly visible on the graph, panels are separated by the vertical dashed line. They also mark the discontinuities in the quarterly data. The sample of workers is aggregated to months and then quarters, discarding months without all rotation groups results in missing quarters between panels. The change in occupation classification in 2004 may additionally drive the sharp discontinuity between 2001 and 2004 panel. One of the things that motivate the displaced workers with high exposure to switch their occupations is the shift in demand for those jobs. In 3.2b it becomes clear that employment share of occupations imperilled by automation

Figure 3.2: Employment share of occupations with high/low automation exposure and occupational mobility of all groups, SIPP 1996-2012



(a) Occupational mobility, all occ.

(b) Employment share

shrinks steadily from 1990s. Moreover, net mobility in those occupations is negative, what means that the inflow does not offset the outflow from those occupations.[16]

3.2.4 Automation and Routinization

One potential concern regarding the measure of exposure to automation and the process itself is its relation to technological change known as skill-biased or routinization. When it comes to the nature of the process, the two phenomena are similar, there are however important empirical differences that should be addressed. Both automation and routinization require some tasks or their parts being commissioned to either computers, robots or some other forms of capital. The difference between the two consist in the scope of activities that can be replaced within a job. Recall from Autor et al. (2003) that routinization was mainly due to the increase in the number of computers that were performing tasks done previously by clerical or administrative workers. Automation encompasses the use of industrial robots: machines that can perform sequence of complex tasks without human operator. The latter requirement is the key to the difference between the two processes: computers could not complete all tasks within a job, whereas multipurpose and reprogrammable machines that do not need human operator can. The threat of some occupations disappearing is hence higher in case of automation. In other words, automation is more labor-displacing phenomenon that routinization, as hinted by Bessen et al. (2019). The alternative task-based measure points that in extreme cases, up to 75% of job activities may be replaced by industrial robots. Statistics presented in Section 3.2.3 show that the workers exposed to automation are typically low-skilled with significantly lower educational attainment than their counterparts with low risk of automation. On the

[16]Net mobility is defined as in Kambourov and Manovskii (2008), presented in Appendix C.4.

contrary, jobs that were subject to routinization were mostly clerical and manufacturing ones from the middle of skill distribution (Figure C2). The difference also stems from the particular industries and occupations that were part of both processes. As already noted, routinization prevailed mostly among clerical occupations, whereas automation, by definition, is heavily concentrated in manufacturing occupations (machine operators, production workers, handlers, etc.). All those differences lead to very weak correlation of the automation and routine indices: 0.1.

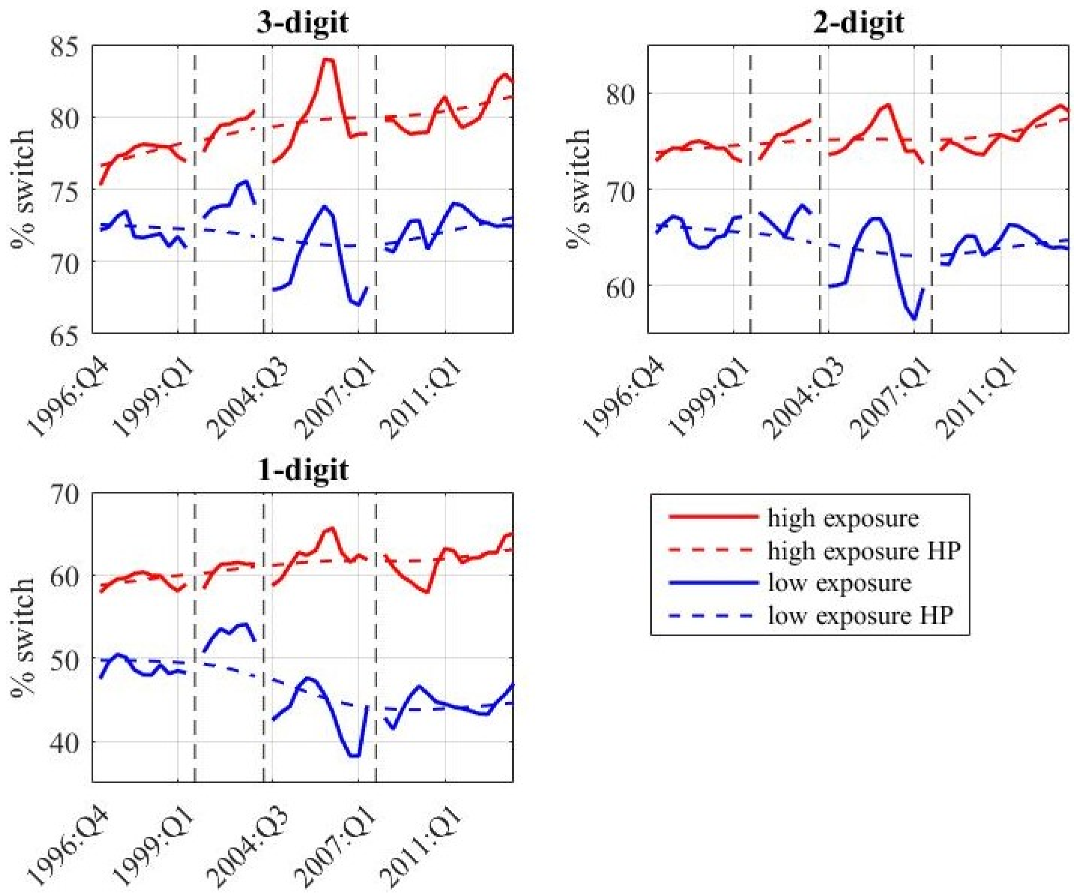
3.3 Empirical Motivation

In this section I discuss the empirical regularities that motivate the paper. All of them are novel findings, that can be categorized into two main sections: occupational mobility during non-employment and wage profile after re-employment. The first subsection uncovers that non-employed workers with high exposure to automation are in fact switching their occupations with higher frequency than remaining groups, with positive and significant trend over the period of study. The increase in mobility is mostly concentrated at the bottom of wage distribution within prior occupation. Upon mobility and re-employment, wages of individuals employed prior to non-employment in occupations with high risk recover slower than of their counterparts with low exposure. The findings are robust to different model and sample specifications as well as exposure measure, the additional checks are presented in the Appendix C.4.

3.3.1 Occupational Mobility

The main focus of the paper is the mobility of workers in the occupations threatened by technological progress. Figure 3.3 presents the aggregate, quarterly evolution of occupational mobility of non-employed workers, depending on their occupation prior to the non-employment period. Digit levels are distinguished for Census occupation classification, SOC class digits yield very similar results. Figure 3.3 unveils two main facts that characterize the level and trend of occupational mobility of non-employed workers. First, individuals employed prior to displacement in occupations with high exposure have noticeably higher mobility levels in each digit classification. Second, there is clear and significant upward trend in mobility of workers exposed to automation. Workers in occupations that decrease employment share due to technological change may be pushed out of their occupation and forced to seek employment opportunities in other jobs. As a result, technological change may lead to involuntary occupational mobility. At the same time workers with low exposure to automation do not reveal any clear trend. One of the possible explanations for the observed mobility of workers exposed to automation might be the already mentioned lower demand for those jobs. Displaced individuals face tight

Figure 3.3: Occupational mobility by digit level. SIPP 1996-2013



NOTE: Vertical dashed lines mark distinct SIPP panels. HP is the Hodrick-Prescott filter.

labor market and decide to change their occupation as an outside option to extending the unemployment spell. On the other hand, they may anticipate that eventually their jobs will be replaced by robots and decide to switch the occupation beforehand. Other category of jobs that are influenced by technological change are routine occupations.[17] Appendix C.4 documents occupational mobility of workers in routine occupations (Figure C5). There is difference in level of mobility between routine and non-routine individuals that becomes negligible for 1-digit level. Moreover, there is no clear trend for either of occupation categories.

Table 3.4 confirms previous findings: displaced workers in occupations exposed to automation have significantly higher mobility on all digit levels. The probability of switching the broad occupation category (1-digit level), conditional on non-employment period, is 9.9 p.p. higher for those who prior to the spell worked in occupation susceptible to automation. Moreover, in all cases there is significant upward trend. The results for oc-

[17] Automation and routinness differ in several aspects. The latter impacts mostly jobs in the middle of skill distribution that are subject to computerization (clerical, administrative support, etc.), whereas the former, defined as industrial robots, refers to manual task-intensive jobs in the bottom of skill distribution.

Table 3.4: Occupational mobility and exposure to robots - (SIPP 1996-2013, E$\not{E}$E spells)

Dep. variable:	1 - digit		2 - digit		3 - digit	
Occ. Mobility	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	0.145	0.099	0.122	0.093	0.086	0.062
	(0.008)	(0.015)	(0.007)	(0.014)	(0.007)	(0.013)
Time	-0.004	-0.006	-0.005	-0.007	-0.005	-0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Exposed $\times$ *Time*		0.005		0.003		0.003
		(0.001)		(0.001)		(0.001)

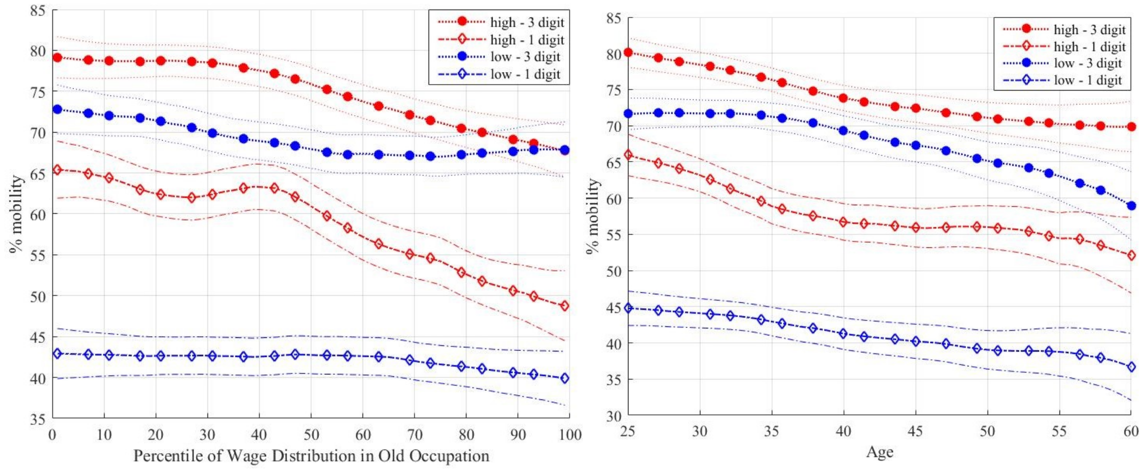
NOTE: Sample size $N = 17,731$, it contains the cross-section of E$\not{E}$E transitions. The dependent variable takes value one if worker changed her occupation during non-employment spell and zero otherwise. Control variables include gender, age, its square, duration of non-employment spell, education level (less than high school, high school, some college and graduate degree), state of residence, interaction of time and age, education level. All observations are weighted by the longitudinal weight.

cupational mobility are robust to econometric checks within education, gender or unemployment spell groups as well as additional controls. Similar patterns can be distinguished in other datasets, e.g. Linked CPS. Robustness checks and results from other datasets are presented in Appendix C.4. One of the threats posed to the findings is that the occupations with high risk of automation may have traditionally high mobility of workers and the exposure measure accounts for persistent mobility patterns rather than automation. The level of reallocation by broad occupational categories (Table C7) indicates that the clerical, sales workers and managers are the biggest contributors to mobility among the displaced workers. Final sample is conditional on the change of employer and panels prior to 1996, due to different methodology of denoting the employer change, are not suitable for the mobility analysis. Similarly, neither linked CPS allows for longer time series, the variable describing change of employer was introduced in 1994. To extend the time series and check if in 70s and 80s there were similar patterns, I use linked CPS without conditioning on the change of employer.[18] From Figure C14 it becomes clear that the difference between the mobility of high and low exposure workers started growing in the mid-1990s (or beginning od 1990 for 1-digit level). Prior to that there is no significant difference between the two considered groups of workers. The widening of the gap in the 90s coincides with introduction of the first industrial robots in selected industries.[19]

[18]The strategy is similar to Carrillo-Tudela and Visschers (2020), who look at the sample of non-employment spells where prior to re-employment individual experienced a month of unemployment. Linked CPS allows to distinguish monthly non-employment periods, however, the structure of the interviews (4 months of interviews - 8 months of break and 4 months of interviews) does not allow to measure complete spells.

[19]The IRF data on the stock of industrial robots starts in 1993 for selected European countries, however in 1993 some industries had already substantial usage of the machines. In particular, the 30th percentile of robots per thousand of workers in 9 European countries was 8.64 in automotive and 4.1 in metal machinery

Figure 3.4: Occupational mobility by wage distribution within occupation and age, 1996-2012 SIPP



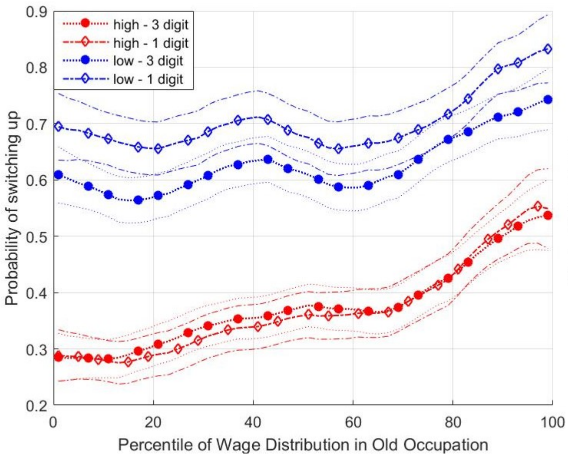
(a) Wage Distribution

(b) Age

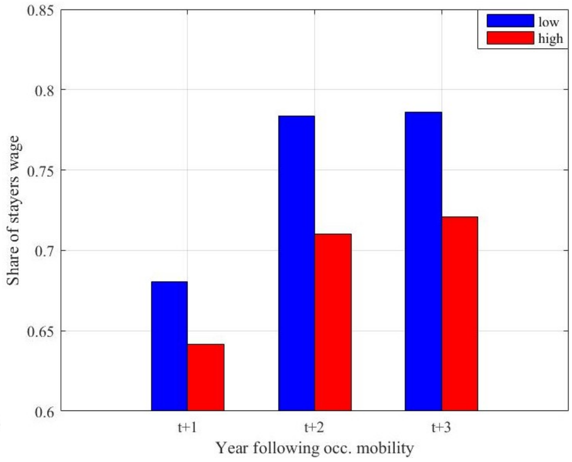
Occupations exposed to automation are typically concentrated at the bottom of skill distribution and in the middle of wage distribution. The literature on occupational mobility (e.g. Groes et al. (2015)) reports the U-shape of occupational mobility as a function of wage prior to transition. This poses a question if in fact the mobility at the bottom of wage distribution is caused by the workers in occupations exposed to automation. To assess the scale of involuntary mobility driven by technological progress, Figure 3.4 plots the occupational mobility for percentiles of wage prior to non-employment (within occupation and year) using kernel smoothed local regression approach with bandwidth of 5 percentiles. First striking feature of 3.4a is the lack of U-shaped mobility. Note however, that our sample contains occupation switches conditional on the non-employment period and the change of employer. Without those two restrictions, SIPP data is able to replicate the U-shape. Within occupation and year, higher occupational mobility of occupations exposed to automation is driven mainly by the workers at the bottom of wage distribution prior to non-employment period. The gap widens for lower digit levels. The automation may thus work similarly to the 'cleansing' effect of business cycle in standard matching framework described by Mortensen and Pissarides (1994): it destroys bad matches. As already mentioned, one of the driving forces occupational mobility is learning about own abilities. It explains the life-cycle effect: higher mobility of young workers. To examine whether the excessive mobility is not caused by learning, Figure 3.4b plots the life cycle of occupational mobility using local regression approach. Indeed, both for high and low exposure displaced workers the life-cycle effect is preserved, however, at any age those imperilled by automation have higher levels. Interestingly, the gap widens for young workers and those close to the retirement, suggesting the role of both mechanisms:

industry. For more details look at Table C1.

Figure 3.5: Probability of switching into occupation with higher average wage than the occupation prior to non-employment period and wage profiles of displaced workers. 1996-2012 SIPP



(a) Direction of Mobility



(b) Wage Profile

learning and automation among labor market entrants.

Note that so far, all of the presented findings are conditional not only on the change of employer by also on the non-employment period longer than 3 weeks. What happens once we include the EE transitions in the sample? First, let's look at the occurrence of job-to-job transitions for low and high automation risk workers (Figure C15). Both high and low exposure workers have similar share of EE transition, suggesting that the former do not anticipate the automation and do not strategically switch employers or occupations. Focusing only on the EE transitions (Figure C8), the main findings of the section are not confirmed. In other words, not only the exposed workers do not switch employers more frequently, but also their mobility is conditional on the non-employment period, suggesting the involuntary reallocation. The results for both EE and E$\not{E}$E transitions remain in line with main findings, for more details see Appendix C.4.

3.3.2 Wage Profile and Direction of Mobility

The occupational mobility is a costly decision that may distort wage profile of displaced workers. Groes et al. (2015) document that even in the fifth year following the mobility, wages of workers who switched to lower ranking occupation hardly reach 0.95 of the wages of workers who stayed in their prior occupations. In the following subsection I first document the direction of mobility depending on the exposure to automation and later focus on the wage profiles of displaced workers.

Direction of Mobility

Unlike in the case of routinization in 80s and 90s, workers exposed to automation do not switch to any particular occupational category. The higher incidence of switches into machine operators, precision production or handlers, and lower incidence of sales, managers or clerical occupational categories suggest that workers in occupations with high risk of automation tend to remain in the categories close to their former. To study the direction of the switch in greater detail I first classify the occupations by average wages and then compare the rank of occupations prior and after the non-employment spell for high and low exposure workers.

Figure 3.5a plots the probability of switching to the occupation with higher average wage in the similar local regression fashion as in previous section. Thanks to (Groes et al., 2015) we know that the probability of moving up the wage ladder is increasing with the wage percentile prior to the non-employment. The distinction of high and low exposure workers reveals striking difference in probability of going up the wage ladder. Individuals displaced from occupations with high risk of automation have significantly lower probability of switching to occupation with higher average wage than their previous one. The difference persists for each wage percentile. Only the exposed workers from the top 10th percentile have the probability higher than 50%. They may be the group identified previously by Battisti et al. (2017) (hereafter BDS) in the context of skill-biased technological change. Using the German administrative records BDS show that some part of workers subject of routinization retrain and are able to move to jobs with more abstract skill content.

The share of those who retrain and move to occupations with higher cognitive requirements may be also identified in the case of automation. Figure C14 compares the cognitive and manual task intensity of occupations prior and after the non-employment spell for the considered sample of transitions. In general, workers exposed to automation tend to downgrade in both dimensions: they switch into occupations with lower cognitive and manual skill intensities. Despite the downward mobility pattern, exposed workers in top 20th percentile of wage distribution tend to move to the jobs with higher cognitive requirements, the automation counterparts of workers identified by BDS. Share of the workers who upgrade in cognitive dimension is relatively small, what may reveal the nature of automation: large differences in training requirements between jobs displaced and created by industrial robots.[20] The analysis of mobility direction reveals potentially alarming patterns: workers from the bottom of skill distribution tend to go down the wage ladder and switch from middle wage occupations to low wage ones.

[20] An illustrative example may be machine operators in automotive industry: jobs created by introducing industrial robots in the plant require skills in robot installing and programming. The latter are the usual STEM occupations, hardly available for untrained machine operator.

Wage Profile

Equally important to direction of mobility are the wage profiles and the persistent distortions in earnings profiles of displaced workers. To determine the wage profiles of workers depending on their level of exposure to automation, I distinguish two types of individuals: i) stayers and ii) movers. The former are the employed workers who in year t didn't change their employer nor experience non-employment period, whereas the latter are individuals who experienced non-employment period and eventually got re-employed at time t. For each year t I distinguish panel of stayers' and movers' earnings with the follow up in $t+1$, $t+2$ and $t+3$ (for longer SIPP panels). Earnings are then aggregated by occupation and time from the event using as weight the share of each occupation in the panel of transitions. Figure 3.5b compares the average weekly real wages of movers and stayers within each occupation for high and low exposure occupations. Workers employed prior to non-employment period in occupations with high risk of automation were not only switching to occupations with lower average wage, but also earning significantly less than their counterparts in low exposure occupations in all periods following the re-employment. Their wages didn't recover after 3 years, being on average 0.72 of the wages of those who stayed in the occupation. Moreover, the difference between high and low exposure workers recovery kept increasing. Looking into hourly wages or distinguishing balanced vs. unbalanced panel does not change the results.[21]

3.3.3 Alternative Measures

The alternative measures of exposure to automation deliver fairly similar results as the baseline specification. All of the results are presented in Appendix C.4.1. The measure based on Frey and Osborne (2017) departs from findings of previous sections as the displaced workers with high exposure do not have initially higher mobility levels. The lack of difference in level may stem from the differences in the occupation categories that prevail in both measures. The alternative measure is more forward-looking and comprises selected service occupations. The positive and significant trend remains unchanged.

3.4 Theoretical Framework

The following section outlines the discrete time random search and matching model with technological acceleration, segmented labor markets and human capital accumulation. The importance of non-employment periods, stressed in the empirical findings, motivates

[21] SIPP panels allow to construct maximum 4-year panels, hence, within each SIPP panel, the last possible period after re-employment is $t+3$. The balanced panels are those where we can observe earnings from t to $t+3$ in all panels from 1996 to 2008. The unbalanced panels mix the cohorts, taking both cohorts that can be observed in 3, 2 and 1 year following the re-employment.

the use of model with labor market frictions. I build on the technological obsolescence approach proposed by Violante (2002), Postel-Vinay (2002) and later developed by e.g. Michelacci and Lopez-Salido (2007). It studies the technological progress in the economy with labor frictions. Risk-neutral workers are matched with jobs that resemble certain technology or machines that age with tenure. Key ingredient of the model is technological distance between two machines of different vintage. It depends on the speed of technology growth, usually represented by the relative price of equipment. The following model departs from previous literature with respect to the measure of technological speed and proposes average change of stock of industrial robot as a proxy for technical acceleration. The logic is the following: matches in occupations with large increase in stock of robots are the ones with larger technological distance between two vintages. They become technologically obsolete faster than other jobs, what may lead to match destruction due to negative surplus of a match. In other words, the average yearly growth of stock of robots measures the rate of labor-displacing technology growth, key ingredient of unemployment shock. Upon displacement, workers face the decision whether to stay in their occupation or not. The reallocation decision is costly, as they lose part of their accumulated human capital and are forced to stay unemployed at least one period more.

3.4.1 The Economy

Time is discrete. The economy consists of finite number of islands (occupations) $\mathcal{O} = \{1, 2, ..., O\}$. Within each occupation $o \in \mathcal{O}$ there is a mass of risk-neutral workers and firms. Workers can die (retire) each period with certain probability ξ. Jobs within an occupation and given human capital level, formed at the same period are identical. The match technology is set at the time of establishing it and is fixed. Workers are ex-ante homogeneous, however while employed they accumulate occupation specific human capital. Match output is a function of match technology and human capital of a worker.

Match Technology. In each occupation $o \in \mathcal{O}$, technology grows at some constant rate $\gamma^o > 0$. The frontier technology in occupation o at time t is denoted as $z_t^o = (1 + \gamma^o)\ z_{t-1}^o$. The technology of a match established τ periods ago (or alternatively: of tenure τ) is defined as $z_{t-\tau}^o$. For simplicity, I assume that firms cannot update their technology, endogenous decision on match technology will be modelled in the next stage of the project. The technological gap is defined as the difference between frontier and match technology:

$$\tilde{z}_\tau^o = z_t^o - z_{t-\tau}^o = (1 + \gamma^o) z_{t-1} - z_{t-\tau}^o = [(1 + \gamma^o)^\tau - 1] z_{t-\tau}^o$$

where τ is job tenure. Note that technological gap grows faster in the occupations with higher γ^o, i.e. where job replacing technology advances more rapidly.

Human Capital. Workers differ with respect to their occupation-specific human capital. They accumulate human capital h_x by learning-by-doing. The set of possible levels of human capital is discrete, $h_x,\ x \in \mathcal{X} = \{1, 2, ..., X\}$ where $X < \infty$. Each period employed worker increases her human capital with probability φ^o. The probability of increasing the level of human capital by one step is occupation specific and defined as $\varphi^o(h_{x+1}|h_x) = 1 - \varphi^o(h_x|h_x)$. During unemployment spell human capital depreciates at rate ζ. Unemployed workers are assigned to their occupation prior to displacement with the unchanged level of human capital. In this simple framework the accumulation of human capital does not differ across different levels of human capital, in other words returns to occupational experience are linear. Imposing non-linear returns to occupational experience (known from the empirical literature) is an interesting extension for the future steps.[22]

Task transferability is a key feature of the model determining the wage profile of a worker who decides to reallocate. Upon change of occupation, workers loose some part of their human capital. The distance function $d_{oo'}(h_x)$ governs the loss of human capital while reallocating from occupation o to $o' \neq o$ with the human capital level h_x in the former. The new level of human capital after the mobility is $\widetilde{h} = d_{oo'}(h_x)$. One can think of $d_{oo'}(\cdot)$ as a step function which tells if, upon reallocation, human capital depreciates by one step while changing from occupation o to o'. The details of the distance function are presented in the Appendix C.5.3. For the simplicity, the distance matrix that measures the proximity between each pair o and o' (where $o \neq o'$) is symmetric, i.e. switching to occupation o' with higher skill requirements is as costly as switching from o' to occupation o with lower requirements.

Match Output. Each agent - firm match produces output which depends on two main factors: $i)$ technological gap of a match with tenure τ in occupation o and $ii)$ the level of worker's human capital (h_x):

$$q^o(\tau, h_x) = (1 + \gamma^o)^{-\tau}\ (l + h_x) \quad , \tag{3.2}$$

where $l = 1$ is a unit of human labor. The first term of 3.2 is a 'penalty' for technological obsolescence. The older is the match, the higher is technological gap which is reflected in the output. On the other hand, the force that can counter the output loss associated with technological gap is the human capital accumulation. Given the probability of increasing human capital level, $\varphi^o(h_{x+1}|h_x)$, individuals stochastically increase their human capital in finite number of periods. The interaction between the two will determine the loss/gain in output with tenure. At the extreme, it can lead to endogenous separation of worker and firm if the value of the match falls below the outside option of the agents (respectively unemployment and vacancy).

[22]E.g. *Kambourov and Manovskii* (2009) document that returns to occupational tenure are non-linear. Higher powers of occupational tenure variable (in this case 2nd and 3rd power) have significant coefficients both in the baseline and IV model.

Matching. Labor market in each island is segmented into finite number of submarkets, one for each pair (o, h_x), where $o \in \mathcal{O} = \{1, 2, ..., O\}$, h_x $x \in \mathcal{X} = \{1, 2, ..., X\}$ and $X < \infty$. Each labor market (o, h_x) resembles standard Diamond-Mortensen-Pissarides model, with constant returns to scale matching function $m(u^o_{h_x}, v^o_{h_x})$. All labor markets have the same matching technology. In each of these markets there is free-entry condition with the cost of posting a vacancy given by κ. The tightness of market (o, h_x) - $\theta^o_{h_x}$ is defined as the ratio of vacancies $(v^o_{h_x})$ and unemployed $(u^o_{h_x})$ in this market. The matching probabilities for workers and firms are respectively $\lambda(\theta^o_{h_x}) = m(u^o_{h_x}, v^o_{h_x})/u^o_{h_x}$ and $\phi(\theta^o_{h_x}) = m(u^o_{h_x}, v^o_{h_x})/v^o_{h_x}$, where $u^o_{h_x}$ and $v^o_{h_x}$ are the mass of respectively unemployed and vacancies in labor market (o, h_x).

3.4.2 Agent's Decisions

Worker's Problem. First, let's consider a worker employed in occupation o after τ periods of job tenure with the level of human capital h_x. The wage $w^o(\tau, h_x)$ is a function of worker's human capital in occupation o and technological gap given τ periods of tenure. The model abstracts from search on-the-job, workers and firms can be separated with exogenous probability δ. The reason behind not including on-the-job search is that in the data I do not observe increase in EE transitions for workers exposed to automation, conditional on job-to-job switch they do not change their occupations more frequently than workers with low exposure. In that sense, exposed workers do not behave strategically, they do not learn about their occupation's exposure to robots. The value function of employed worker at the production stage is then:

$$\begin{aligned} W^o_t(\tau, h_x) =& w^o(\tau, h_x) + \beta\ (1 - \xi)\ \mathop{\mathbb{E}}_{h_{x'}} \Big[(1 - \delta)\ (1 - \psi^o(\tau', h_{x'})) \\ & max\big\{W^o_{t+1}(\tau', h_{x'}), U^o_{t+1}(h_{x'})\big\} + [(1 - \delta)\ \psi^o(\tau', h_{x'}) + \delta]\ U^o_{t+1}(h_{x'})\Big] \quad , \end{aligned} \tag{3.3}$$

where β is a discount factor, $(1 - \xi)$ a probability of surviving to the next period, $x' \in \{x, x + 1\}$ and tenure evolves deterministically $\tau' = \tau + 1$. Job destruction caused by technological progress is captured by $\psi^o(\tau', h_{x'})$. It is an indicator defined as $\psi^o(\tau, h_x) = \mathbf{1}\{S^o_t(\tau, h_x) \leq 0\}$, where $S^o_t(\tau, h_x) = W^o_t(\tau, h_x) - U^o_t(h_x) + J^o_t(\tau, h_x)$ is a match surplus. Next period, if the match is not destroyed by exogenous forces, workers observe their human capital $h_{x'}$, and choose whether to stay in their current job with the utility level $W^o_{t+1}(\tau', h_{x'})$ or become unemployed in their occupation o and receive $U^o_{t+1}(h_{x'})$. Given the realization of $h_{x'}$ workers and firms can endogenously separate if their match value falls below the outside option. Given the possible endogenous separation let's define the policy function $\mathscr{I}^W$:

$$\mathscr{I}^W(\tau, h_x) = \begin{cases} 1 & \text{if} \quad W(\tau, h_x) < U(h_x) \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

Once unemployed, the worker has two possible choices: $i)$ either stay in her occupation o and search for a job or $ii)$ change the occupation to some $o' \neq o$. In the latter case I assume that individuals cannot change the occupation and search for a job in the same period. First, they spend one period unemployed in the new occupation and in the following period search for a job. It can be interpreted as the additional cost of occupational mobility. The unemployed worker receives some unemployment insurance b. Additionally, I distinguish both endogenous and exogenous reallocation across islands. The latter captures the flows that originate from motives and productivity differentials not captured by the model (e.g. learning about own abilities). The value function of unemployed worker is:

$$\begin{aligned} U_t^o(h_x) = b + \beta\,(1-\xi)\ \underset{h_{x'}}{\mathbb{E}} \Big[\sum_{o' \neq o} s_{oo'} \ \Big(\pi_{oo'}\ U^{o'}(h_{x'-1}) + (1-\pi_{oo'})\ U^{o'}(h_{x'}) \Big) \\ + \big(1 - \sum_{o' \neq o} s_{oo'}\big) \max \Big\{ \mathcal{R}_{t+1}(h_{x'})\ ,\ \lambda(\theta^o_{h_{x'}})\ \max\{W^o_{t+1}(0, h_{x'}), U^o_{t+1}(h_{x'})\} \\ + (1-\lambda(\theta^o_{h_{x'}}))\ U^o_{t+1}(h_{x'}) \Big\} \Big] \end{aligned} \tag{3.5}$$

where, upon survival, $x' \in \{x-1, x\}$ depending on the realization of human capital that depreciates while unemployed with probability ζ. Unemployed workers can be reallocated exogenously to occupation o' with probability $s_{oo'}$. The loss of human capital while reallocating from island o to o' is governed by the parameter $\pi_{oo'}$. It is the probability that after switching island o to o' worker's human capital depreciates by one step. With probability $(1 - \pi_{oo'})$ they stay at the same level of human capital in new occupation o'. The second term in the brackets is the value for those who weren't exogenously reallocated. They can decide whether to search for a job in their own island or reallocate to other occupation. The value upon reallocation is defined using the reallocation function $\mathcal{R}_{t+1}(h_x)$. It is defined as:

$$\mathcal{R}_t(h_x) = \max_{o' \neq o}\{\pi_{oo'}\ U^{o'}(h_{x-1}) + (1-\pi_{oo'})\ U^{o'}(h_x)\} \tag{3.6}$$

where workers still face probability of loosing human capital during reallocation - $\pi_{oo'}$. I assume that the workers have knowledge on the market tightness in all of the remaining submarkets. Given the human capital loss probabilities $\Pi = \{\pi_{12}, ..., \pi_{oo'}, ..., \pi_{O\,O-1}\}$ and the probability of human capital depreciation while unemployed (ζ), human capital can depreciate up to two steps while reallocating from island o to o'. Note that in case the unemployed worker stays on the same island, receives an offer in her submarket and decides to form a match, the technological gap is set to zero (as $\tau = 0$). Similarly to employed worker case, the policy function $\mathscr{I}^{\mathcal{R}}(h_x)$ can summarize the decision of unemployed worker whether to stay in her occupation or move to the one that maximizes her unemployment value, whereas $\mathscr{I}^{U}(h_x)$ determines whether, conditional on receiving a job offer, individuals choose to establish a match.

Firm's Problem. Consider firm in occupation o with a job filled by a worker with human capital level h in a match established τ periods ago. It's expected lifetime discounted profit is:

$$J_t^o(\tau, h_x) = q^o(\tau, h_x) - w^o(\tau, h_x) + \beta \underset{h_{x'}}{\mathbb{E}} \Big[(1-\delta)(1-\psi^o(\tau', h_{x'}))\ max\{J_{t+1}^o(\tau', h_{x'}), 0\}\Big] \tag{3.7}$$

where δ is exogenous job separation probability. The first two terms on right hand side of (3.7) describe firm's profit: output ($q^o(\tau, h_x)$) net of worker's wage ($w^o(\tau, h_x)$). If the match is not subject to job destruction (captured by $\psi^o(\tau', h_{x'})$ and exogenous separation probability δ), and due to realization of $h_{x'}$ the match value falls below its outside option, the firm decides to separate. Similarly to workers, we can define firm's policy function $\mathscr{I}^{J}(\tau, h_x)$:

$$\mathscr{I}^{J}(\tau, h_x) = \begin{cases} 1 & \text{if} \quad J(\tau, h_x) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

Once match is destroyed, firms decide to post a vacancy. A vacant firm posting the offer on the submarket (o, h_x) has the expected utility:

$$V_t^o(h_x) = \max\big\{ -\kappa + \beta\ \phi(\theta_{h_x}^o)\ \max\{J_{t+1}^o(0, h_x), 0\}, 0\big\} \tag{3.9}$$

where κ is a cost of posting a vacancy, $\phi(\theta_{h_x}^o)$ is a probability of finding a worker in occupation o with human capital level h_x. If the match is established, the technological gap is 0, hence $\tau = 0$.

Wages. I assume that wages are determined by Nash Bargaining. Consider a match (τ, h_x) in occupation o. Then, the wage $w^o(\tau, h_x)$ is the solution of:

$$(1-\alpha)\Big[W_t^o(\tau, h_x) - U_t^o(h_x)\Big] = \alpha\ J_t^o(\tau, h_x) \tag{3.10}$$

where $\alpha \in (0, 1)$ the exogenous bargaining power of a worker, whose outside option is $U(h_x)$. Wages are re-negotiated each period after realization of human capital h_x. The match surplus is defined as $S_t^o(\tau, h_x) = W_t^o(\tau, h_x) + J_t^o(\tau, h_x) - U_t^o(h_x)$.

Timing. After the realization of human capital, the model is divided into four stages: $i)$ *separation* $ii)$ *reallocation* $iii)$ *search* and $iv)$ *production*. At the beginning of each period both employed and unemployed workers first update their human capital. Upon observing the new human capital level $h_{x'}$, matched workers and firms re-negotiate the wage $w^o(\tau, h_{x'})$ given the Nash bargaining rule (3.10). If the outside option for worker is higher than the value of continuation of the match, they decide to separate. If the match is preserved, it produces output $q^o(\tau, h_{x'})$.

3.4.3 Equilibrium Conditions

Equilibrium consists of value functions $\{W(\tau, h_x), U(h_x), J(\tau, h_x)\}$, worker's policy functions $\{\mathscr{I}^W(\tau, h_x), \mathscr{I}^{\mathcal{R}}(h_x)$ and $\mathscr{I}^U(h_x)\}$ (i.e. separation , reallocation and employment decisions), firm's policy function $\{\mathscr{I}^J(\tau, h_x)\}$ (layoff decision), laws of motion of $\{h_x\}$, law of motion of the distribution of unemployed and employed workers, vector of market tightness $\{\boldsymbol{\theta} = (\theta_1, ..., \theta_o, ..., \theta_O)\}$, vector of wages $\{\boldsymbol{w}(\boldsymbol{\tau}, \boldsymbol{h})\}$, such that:

(i) Value functions and decision rules follow from the firm's and worker's problems described by (3.3),(3.4),(3.5), (3.7) and (3.8).

(ii) **Free-entry** condition holds.

(iii) Wages $w(\tau, h_x)$ solve **Nash bargaining** formula given by (3.10):

$$w^o(\tau, h_x) = \alpha\ q^o(\tau, h_x) + (1-\alpha)\ b - (1-\alpha)\ \beta\big[\underset{h_{x'}}{\mathbb{E}}\ U^o_{t+1}(h_{x'}) - \mathcal{C}^o(\widetilde{h_x})\big] \quad ,$$

where $\mathcal{C}^o(\widetilde{h_x})$ is a function of future unemployment given the reallocation function $\mathcal{R}(h_x)$ and tightness on the market (o, h_x).[23]

(iv) Law of motion of employed and unemployed workers is described by (C.3), (C.4) and (C.5).

3.5 Quantitative Analysis

The following section outlines the calibration strategy, moments used in the estimation and the results of the first, preliminary calibration of the model. The quantitative analysis is currently main challenge of the project and will be subject to changes in the near future.

3.5.1 Calibration Strategy

In the first, simplified version of the model, there are six islands (i.e. $o \in \{1, ..., 6\}$) that resemble main occupational category groups: Professionals (1), Clerks (2), Sales (3),

[23]More precisely, $\mathcal{C}^o(\widetilde{h_x})$ is given by the formula $\mathcal{C}^o(\widetilde{h}) = max\{\ \mathcal{R}_{t+1}(h_x) - c, \lambda(\theta^o_{h_x}) \max\{W^o_{t+1}(0, h_x), U^o_{t+1}(h_x)\} + (1-\lambda(\theta^o_{h_x}))U^o_{t+1}(h_x)\}$.

Table 3.5: Targeted moments

Avg. job finding rate $(\hat{UE})$	*Returns to job tenure:*
Avg. separation rate $(\hat{EU})$	*- 0-5 years*
Occ. mob.$_{oo'}$ $(U^o\hat{U}^{o'})$	*- 5-10 years*
Elasticity of job finding rate $(\hat{\eta})$	*- 10-15 years*
Home production $(\hat{b})$	*Vacancy cost* $(\hat{\kappa})$
Returns to occ. experience	*Wage loss of occ. mobility*

NOTE: The moments for occupational mobility are computed for all mobility flows between occupations o and o', where $o \neq o'$. In total there are 30 moments for occupational mobility between 6 occupations. Returns to occupational experience are a vector with 6 elements, similarly to wage loss while unemployed. Wage loss of occupational mobility is the ratio of the wage of occupational 'stayers' and 'movers' one year after re-employment of the latter.

Services (4), Production (5), Transport and Handlers (6). Period of the model is half of the year with maximum age of the technology corresponding to 15 years.[24] The death rate ξ is set to 0.0125, to match the average labor market experience of 40 years. There are three levels of human capital, $h = \{h_1, h_2, h_3\}$ where $h_3 < \infty$. The probability of increase in human capital, φ^o is a vector of 6 parameters, estimated in the calibration. The probability of skill loss while reallocating, $\pi_{oo'}$, is governed by the occupational distance matrix, computed from O*NET database. The distance between occupation o and o' is defined as the average difference in manual and cognitive task intensity between the islands and ranges between 0 and 1. For more detailed description of the distance matrix see Appendix C.5.3. Human capital may depreciate while unemployed, the depreciation rate, ζ, is estimated in the calibration. Unit of human labor l equals 1 and discount rate is set to match yearly interest rate of 4%. Matching function has a Cobb-Douglas structure with two parameters: $m(u, v) = \chi u^\eta v^{1-\eta}$. Following Pissarides and Petrongolo (2001), bargaining power (α) is set to 0.5, additional condition requires that the bargaining power must be equal to elasticity of job finding rate η.[25] Finally, the growth rates of technology are computed from IFR data. More precisely, the growth rate of technology is the average yearly growth in stock of robots in particular occupation. Occupations are divided into High (island 5,6), Medium (island 1,2) and Low (island 3,4) exposure to job-displacing technology, based on their growth rates. The period of interest is 1993-1996 and the rates are respectively $\gamma^H = 0.0399$, $\gamma^M = 0.0208$ and $\gamma^L = 0.0051$ (i.e. island H is

[24] *International Federation of Robotics* estimates the average life span of the technology (in this case industrial robot) is 15 years. This assumption is based on the results of the UNECE/IFR panel study carried out in 2000 among major robot companies.

[25] Condition $1 - \alpha = \eta$ in the simple matching model is known as Hosios (1990) condition. It forces firms to post the efficient number of vacancies in the submarkets set by occupation and human capital.

Table 3.6: Calibration parameters

Parameter	Description	Value
δ	Exogenous separation probability	0.0286
χ	Matching function parameter	0.5108
η	Elasticity of job finding rate	0.5640
κ	Cost of vacancy posting	0.2326
b	Home production	0.2546
h_1	Human capital, 0-5 years of experience	1.3024
h_2	Human capital, 5-10 years of experience	1.2434
h_3	Human capital, 10-15 years of experience	1.7294
φ_1	Human capital increase proba., occ. group 1	0.0323
φ_2	Human capital increase proba., occ. group 2	0.0297
φ_3	Human capital increase proba., occ. group 3	0.0279
φ_4	Human capital increase proba., occ. group 4	0.0289
φ_5	Human capital increase proba., occ. group 5	0.0599
φ_6	Human capital increase proba., occ. group 6	0.0395
ζ	Human capital depreciation rate	0.0193

occupation with high risk of automation, etc.).[26] Parameters are normalized with respect to match output ($q^o(\tau, h)$). The set of parameters is $\Theta = \{\delta, \chi, \eta, \kappa, b, h_1, h_2, h_3, \boldsymbol{s}, \zeta, \boldsymbol{\varphi}\}$ where $\boldsymbol{\varphi}$ is a vector with 6 parameters and $\boldsymbol{s}$ is a matrix of 30 parameters, resulting in 45 parameters to estimate. To do so I minimise the sum of squared distances between set of moments and their counterparts in the data.

Targeted Moments. Given SIPP panel 1996 I construct a set of moments that exactly identify the vector of parameters $\boldsymbol{\Theta}$ and characterize the labor market in the pre- or early-robot era. Table 3.5 describes moments distinguished to calibrate the model. The exogenous separation probability δ is matched with the average EU flow rate. The matching function parameter χ is informed by the job finding rate (remember that given the matching function, $\hat{\lambda} = \chi\theta^{\eta}$). Parameter η is matched with the elasticity of job finding rate from the literature (following Pissarides and Petrongolo (2001) $\hat{\eta} = 0.5$). Two further parameters, κ and b, are identified using the approach of Hall and Milgrom (2008). The cost of posting a vacancy, κ, is informed by $\hat{\kappa}$ defined as $\hat{\kappa} = \phi(\theta) \times \mathcal{C}$, where $\phi(\theta)$ is weighted average vacancy filling rate and $\mathcal{C}$ is the cost of hire. The cost of hire $\mathcal{C}$ is set according to Abowd and Kramarz (2003) and amounts to 14% of half-year pay per hire.[27] Home production b is captured by $\hat{b}$ equal to 25% of the average wage in the

[26] The rates of technology growth for each island are: $\gamma^1 = 0.0191$, $\gamma^2 = 0.0225$, $\gamma^3 = 0.0025$, $\gamma^4 = 0.0076$, $\gamma^5 = 0.0489$, $\gamma^6 = 0.0309$.

[27] Note that Abowd and Kramarz (2003) find that cost of hire equals 14% of quarterly pay per hire. In this calibration, for sake of simplicity I assume that the same holds for the model period - half of the year.

Table 3.7: Calibrated economy

Targeted moment	Data	Model	Targeted moment	Data	Model
Avg. job find. rate $(\hat{UE})$	0.788	0.789	Ret. to occ. ex. $(o = 1)$	0.145	0.145
Avg. separation rate $(\hat{EU})$	0.061	0.062	Ret. to occ. ex. $(o = 2)$	0.092	0.093
Elast. of job find. rate $(\hat{\eta})$	0.500	0.564	Ret. to occ. ex. $(o = 3)$	0.190	0.190
Home production $(\hat{b})$	0.250	0.252	Ret. to occ. ex. $(o = 4)$	0.130	0.132
Returns to job tenure (h_1)	0.805	0.923	Ret. to occ. ex. $(o = 5)$	0.112	0.112
Returns to job tenure (h_2)	1.020	1.010	Ret. to occ. ex. $(o = 6)$	0.111	0.112
Returns to job tenure (h_3)	1.175	1.090	Wage loss of occ. mobility	0.669	0.604
Vacancy cost $(\hat{\kappa})$	0.233	0.233			

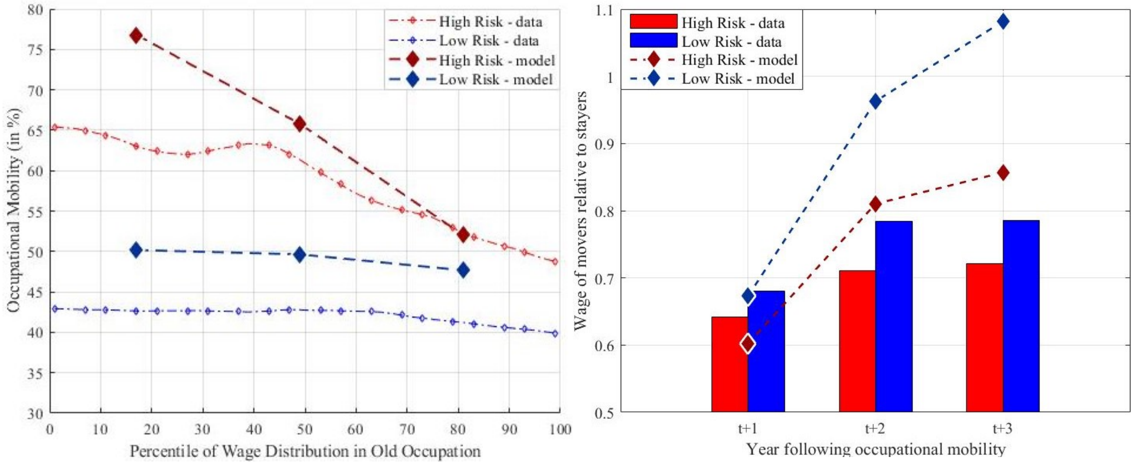
NOTE: the occupational mobility is conditional on the unemployment. The moment for home production $(\hat{b})$ is defined as in Hall and Milgrom (2008) as a ratio of home production b and average wage in the economy. Returns to job tenure are relative to the average wage in the economy, whereas returns to occupational experience are computed following Kambourov and Manovskii (2009). Moment for the wage loss of occupational mobility is computed from the simulation of the calibrated model.

economy. Further, I use the returns to job tenure to discipline the levels of human capital (h_1, h_2, h_3). The human capital levels correspond to respectively 0-5, 5-10 and 10-15 years of job tenure. The vector of human capital increase probabilities, φ, is matched with returns to occupational experience for each occupational group o. Moments are computed similarly to Kambourov and Manovskii (2009). Moment for the rates of human capital depreciation while unemployed, ζ is the wage loss that originates from occupational mobility. In the similar style as in Section 3.3.2, I compute the ratio of wages of occupational 'stayers' and 'movers' one year after occupational mobility of the latter. The details of derivation of returns to occupational experience are presented in Appendix C.5.3. Keep in mind that given limited number of islands and the fact that mobility describes movements between islands, mobility moments from the data have lower values than the ones presented in Section 3.3. The estimated parameters are reported by Table 3.6. The human capital levels $\{h_1, h_2, h_3\}$ are much higher than the one estimated by Carrillo-Tudela and Visschers (2020), however, keep in mind the differences in matched moments, period and skill transferability between the two models.

3.5.2 Fit of the Model

Table 3.7 reports the fit of the initial calibration of the model. All moments, apart from returns to job tenure, occupational experience and income loss, are computed across occupations and human capital levels using respective weights. Returns to job tenure are computed across occupations for given level of human capital. The initial model fits fairly good, especially for the moments describing average job finding rate, average sep-

Figure 3.6: The comparison of the findings: Data vs. Model moments (Facts 2 and 3). Model simulation.



(a) Fact 2.

(b) Fact 3.

aration rate, vacancy cost and returns to occupational experience. Relative wages reveal increasing returns to job tenure, in line with the data. The fit of returns to occupational experience is particularly close to the data. Moments for flow between occupation groups are reported in Table C13 and match the data well. This simple version of the model, with rate of technological growth and various pace of human capital accumulation as the only forces driving productivity differentials across islands, is able to produce substantial share of endogenous separation rates. They account for 19% of all separations. The non-targeted moments are displayed in Table C14. The wage patterns are quite consistent with the data.

In order to study the income loss caused by automation I simulate the model. Figure 3.6 presents the results of 100 simulations of panel of employment history of 10,000 workers. The targeted moments from the simulation match well the ones from the model (see Appendix C.5.3). More interestingly, the life-cycle characteristics of unemployment, mobility rate, UE flows and (to lesser extent) EU flows are preserved. Figure 3.6a shows two key findings: the mobility gap between high and low exposure occupations (Fact 1.) and the lack of U-shape of the mobility (Fact 2.). The wage loss upon the displacement presented by Figure 3.6b documents the third key finding of the empirical part: slower income recovery of workers that are at risk of automation (in the model: occupational groups 5 and 6). The wage profiles were constructed in the same fashion as in the empirical part: by comparing the annual earnings of occupational stayers and movers, where the former were employed in the same occupation throughout the study period, whereas the latter changed occupation at year t.

Table 3.8: Calibrated economy - automation shock

Moment	Data^{2012}	Model^{2012}	Change$^{1996-2012}$	
			Data	Model
Occ. mob.^{H}/ Occ. mob.^{L}	1.509	1.384	$\uparrow 47\%$	$\uparrow \mathbf{37\%}$
Occ. mob.^{H}	0.549	0.606	$\uparrow 14\%$	$\uparrow \mathbf{16\%}$
Wage^H / Wage^L	0.867	0.825	$\downarrow 4\%$	$\downarrow 1\%$
Average Output	-	-	-	$\downarrow \mathbf{2\%}$

NOTE: the occupational mobility is conditional on the unemployment. All data moments are computed from the 2008 panel of SIPP and comprise the data for years 2009-2013. The change is computed with respect to initial steady state (pre-robot period).

3.5.3 Automation Shock

In this simple exercise I simulate the response of the economy to automation shock. All of the parameters, except from the rates of labor-displacing technology growth, remain the same as in the initial calibration. The rates of technology growth take the values for the years 2012-2016, period characterized by high stock of robots in occupations 5 and 6 and steadily increasing implementation on all islands. The rates in the subgroups were $\gamma^H = 0.0869$, $\gamma^M = 0.0230$ and $\gamma^L = 0.0101$.[28] Table 3.8 compares both steady states for the relevant moments (i.e. initial calibration and new equilibrium for the new set of labor-displacing technology growth rates). As a response to the automation shock, the ratio of occupational mobility increases in the model less than in the data (47% compared with 37%), what happens mainly due insufficient decrease in mobility of the unemployed on the islands with low exposure to labor-displacing technology. The mobility on islands at risk of automation increases by similar amount (14% compared with 16%).

The response of relative wages resembles the pattern observed in the data - workers at risk of labor-displacing technology not only reallocate more frequently and have higher EU flows, automation shock reduces their wages by around 1%. The number corresponds to the findings of Acemoglu and Restrepo (2017a), keep in mind however they estimate it for the panel of commuting zones, not workers employment history. The average match output falls by 2 percent, as a result of increase in occupational mobility and skill transferability mechanism. Unemployed workers in occupations with high risk of automation are forced to switch into more distant ones, facing higher probability of human capital loss. In other words they reallocate towards occupations where they are less productive,

[28]The rates of technology growth for each island are: $\gamma^1 = 0.0212$, $\gamma^2 = 0.0248$, $\gamma^3 = 0.0093$, $\gamma^4 = 0.0108$, $\gamma^5 = 0.1159$, $\gamma^6 = 0.0579$.

what lowers average match output.[29] As a result of increase in mobility of workers with high exposure to automation, the average level of human capital drops. The culprit is skill transferability rooted in the reallocation mechanism - while changing an occupation, unemployed workers face probability of loosing part of their human capital. Upon reallocation unemployed workers can loose up to two levels of human capital.

3.6 Policy Implications

One of the most interesting findings of automation shock counterfactual is the loss of average match output due to job automation. Unemployed workers at risk of automation reallocate to different occupations, however due to large drop in human capital they are less productive in the new occupation. Skills they have accumulated in the old job are no longer needed. Hence, the focal point of the following section is the design of benefit or retraining system that would target the output loss and facilitate mobility of displaced workers.

The possible policies include variety of proposals, e.g. various off-the-job trainings, unemployment insurance that depends on the exposure to automation or reduction in mobility costs for displaced workers. Shall we provide them training to reduce the human capital loss, design incentives for displaced workers with high exposure to find a better match (e.g. higher unemployment benefits) or induce them to limit their unemployment spell? Other possible set of policy proposals concerns the transferability of human capital. Off-the job training provided to unemployed workers may contribute to task transferability of human capital. In other words, re-trained workers may be able to find a better match once unemployed. The subsequent policy proposal may target the workers with low level of human capital (potentially young ones) and facilitate mobility into more distant occupations that won't be at risk of automation in the near future. This exercise would prevent young workers to continue switching into close occupations that sool will be subject to automation. All of the aforementioned proposals will be subject of the analysis in the following section.

3.6.1 Off-the-Job Training

First let's examine the policy that would provide re-training opportunities for the displaced workers that are at risk of automation. The unemployed workers become more productive in other occupations, what in turn may attenuate the output loss. The key to training proposal is skill transferability mechanism. In the following exercise I first relate

[29] It becomes clear once you look at the equation 3.2. Match output is a function of human capital. As the automation shock happens, unemployed workers switch to more distant occupations (probability of human capital loss $\pi_{oo'}$ is higher), what results in larger reduction of human capital. The loss is big enough to dominate the lower rates of technology growth $\gamma^{o'} < \gamma^{o}$.

Table 3.9: Calibrated economy - automation shock and policy couterfactuals

	Baseline$^{1996-2012}$		Off-the-job Training		
	Data	Model	Quarter	Half year	Year
Occ. mob.^{H}/ Occ. mob.^{L}	$\uparrow 47\%$	$\uparrow \mathbf{45\%}$	$\uparrow \mathbf{46\%}$	$\uparrow \mathbf{47\%}$	$\uparrow \mathbf{49\%}$
Wage^H / Wage^L	$\downarrow 4\%$	$\downarrow 1.4\%$	$\downarrow 0.3\%$	$\downarrow 0.6\%$	$\downarrow 1\%$
Wage^H	$\downarrow 2\%$	$\downarrow 4\%$	$\downarrow 4.3\%$	$\downarrow 4.4\%$	$\downarrow 4.7\%$
Match output	-	$\downarrow \mathbf{1.6\%}$	$\downarrow \mathbf{1.5\%}$	$\downarrow \mathbf{1.4\%}$	$\downarrow \mathbf{1.3\%}$

NOTE: the occupational mobility is conditional on the unemployment. All data moments are computed from the 2008 panel of SIPP. The change is computed with respect to initial steady state (pre-robot period). The Baseline automation shock differ from Table 3.8 as a result of different skill transferability matrix. Off-the-job training corresponds to limiting the distance in educational requirements between two occupations by quarter, half-year and year respectively.

the probability of human capital loss to the training and educational distance between two occupations. The proposed policies reduce the educational distance between two occupations that correspond to quarter, half-year and a year of off-the-job training. Given the new skill transferability matrices that correspond to providing off-the-job training to displaced workers at risk of automation, I perform the automation shock counterfactual and compare it to baseline results.

The new distance matrix is constructed given the educational requirements in particular occupations. Section C.5.3 discusses in detail the method of deriving the distance matrix. It is defined as the difference in educational requirements (in years) between occupations o and o', standardized so that $d_{oo'} \in (0, 1)$. Give the new distance matrix I recalibrate the model and perform baseline automation shock counterfactual. For the policy counterfactual I perform the automation shock exercise using the skill transferability matrix that limits the educational distance between high risk and remaining occupations by respectively a quarter, half-year and year. Note that in that case the distance matrix is no longer symmetric, as $d_{oo'} \neq d_{o'o}$ if $o \in \{H\}$ or $o' \in \{H\}$.

Table 3.9 compares the results of policy counterfactuals with the baseline one. The results of the baseline automation shock differ from the ones presented in Table 3.8 since they are based on new distance matrix. The findings do not change much, if enything the model explains larger share of increase in mobility gap (around 96%). Non surprisingly, displaced workers with longer off-the-job training increase their occupational mobility. The human capital loss becomes smaller and they find it more profitable to reallocate. What may seem counter-intuitive is the wage loss in high-risk occupations for the longer trainings. This is just the concentration effect, as the workers with higher levels of human capital leave first. More importantly, the output loss decreases with the level of off-the-job training. Providing a training that corresponds to one year of education in the new occupation reduces the output loss by nearly 20%. One can however argue that the most probable level of retraining is the quarterly one, in which case the reduction of output loss is modest.

3.7 Conclusion and Next Steps

To the best of my knowledge, this paper is the first attempt to describe the relationship between job automation and worker reallocation. The empirical analysis aims at studying the role of automation in labor market frictions. Key factor is the pace of implementing industrial robots - significantly higher than during computerization process in 90's. Jobs created and replaced by automation require different set of skills. As a result, workers displaced due to automation face limited job opportunities and may decide to change their occupation. From the existing literature we know that job automation increases the share of exits out of labor force, leading to the drop in employment-to-population ratio and average wages. Novel empirical regularities presented in this work suggest that workers at risk of automation experiencing non-employment spell increase their occupational mobility. Moreover, conditional on mobility, their wages recover slower than of their counterparts with low exposure to automation.

In an attempt to quantify the effect of job automation on occupational mobility, I develop an equilibrium search and matching model with technological acceleration, human capital accumulation and occupational mobility. The key mechanism of the mobility decisions is skill transferability that specifies the level of human capital in the new occupation. The initial calibration matches salient features of the economy with substantial share of endogenous reallocations. In the automation shock exercise, the response of the economy follows patterns observed in the data between 1996 and 2012 with similar magnitudes. The mobility rate of high exposure workers increases by 16% (compared with 14% reported in the data), leading to 1% drop of wages in occupations that experience large increase in the implementation of industrial robots.

The next steps of the project involve further development of the theoretical framework and policy proposals that would offset the wage loss of exposed workers after mobility. The endogenous updating of match technology is one of the major changes worth implementing, along with increase of the number of occupations (e.g. to match 1-digit Census 1990 classification) and human capital levels. The policy proposals will concentrate on the reduction of mobility costs for displaced workers at risk of automation, that stem from skill transferability mechanism and prolonged unemployment spells.

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Chapter A

Appendix to Chapter 1

A.1 Empirical Strategy - Worker Side

A.1.1 Job Tenure

One of the stylized facts of referrals reveals that the referred workers have lower turnover and hence longer job tenure than non-referred employees.[1] Job tenure is often perceived as a sign of match quality. The following exercise aims not only at replicating the findings in the VWH sample, but checking the behavior of linked job-to-job switchers, as the ones with potentially higher skills, higher initial wage and lower turnover. Following empirical literature, I propose Proportional Hazard model with the conditional hazard function. In my model, the conditional hazard function is given by:

$$h(t, \boldsymbol{x}) = \lambda(t)\ exp(\boldsymbol{x}'\boldsymbol{\beta})$$

where $\lambda(t)$ is so called baseline hazard function and $\boldsymbol{x}$ is a matrix of control variables that include worker- and firm-specific characteristics. The model is censored on the right, as some observations end in 2001, tenures are measured in weeks.

A.1.2 Hiring Probability

Social networks may impact individual labor outcomes of workers experiencing exogenous employment shocks. Cingano and Rosolia (2012) find that one standard deviation increase in network employment at the time of a shock reduces unemployment duration by 8%, similarly Glitz (2017) claims that 10 p.p. increase in the one's network employment rate increases re-employment chances by 7.5%. Both works proxied social network with former co-workers and measured employee performance when faced with firm clo-

[1] E.g. Dustmann et al. (2016), Brown et al. (2016).

sure, without distinguishing linked hires. In the spirit of Cingano and Rosolia (2012) and Glitz (2017) in the following part I examine referral heterogeneity at the time of firm closure.[2] The VWH dataset contains precise information on the date of the firm closure, hence first I distinguish establishments that are shut down between 1995 and 2001 and identify workers who lost their jobs due to the closure. I denote a worker as displaced due to firm closure if she lost the job within one year prior to the event. Otherwise, there exists a threat of selection bias, as some of the workers may be better informed about firm condition or have any kind of insight regarding the closure, and leave the company weeks prior to the formal closure. The model is given by:

$$\begin{aligned} Empl\ Proba_i = \delta_0 + \delta_1\ Connected_i + \delta_2\ Empl.\ Rate_i + \delta_3(Connected_i \times Empl.\ Rate_i) \\ + \delta_4\ Jtj_i + \delta_5(Connected_i \times Jtj_i) + \delta_5\ X_i + \delta_6\ W_i + \varepsilon_i \end{aligned}$$

where all of the variables $Connected_i$ and Jtj_i describe if individual i was connected or transitioned job-to-job at the entry to the firm that was later subject to closure. $Empl\ Proba_i$ is an indicator variable that takes value 1 is individual found a job within 26 weeks following the firm closure. To check robustness of the results, the model includes variables describing employment rate within one's network and instrumental variable defined as in Cingano and Rosolia (2012) and Glitz (2017).

[2]Heterogeneity distinguished prior to displacement.

A.2 Additional summary statistics

A.2.1 Employer - Employee Matched Data

Table A1: Basic characteristics of analysed sample, years 1997-2001

	VWH	**AIDA**	**AIDA**	**VWH-AIDA**				
		(raw)	(cleaned)	(raw)	(clean 1)	(clean 2)	(cl1, cont.)	(cl2, cont.)
Firms								
No. firms	48,555	7,537	3,889	6,635	6,467	3,651	4,650	2,379
No. employees	15.5	30.9	55.3	31.8	30.5	51.4	26.2	48.6
	(66.7)	(51.8)	(63.6)	(50.6)	(45.5)	(54.1)	(43.1)	(55.6)
Revenue		7,023	10,847	7,032	6824	9,989	5,846	9,427
(1000's Euros)		(14,413)	(17,710)	(14,146)	(13,012)	(15,333)	(12,011)	(15,654)
Revenue per worker		409	194	374	359	194	361	185
(1000's Euros)		(784)	(168)	(697)	(500)	(169)	(525)	(157)
Added Value		1,509	2,513	1,529	1,466	2,309	1,248	2,171
(1000's Euros)		(3,538)	(3,672)	(3,379)	(2,966)	(3,130)	(2,765)	(3,270)
Added Value per worker		66	43	63	59	43	60	42
(1000's Euros)		(286)	(16)	(76)	(54)	(16)	(56)	(16)
Total Assets		5,931	8,643	5,790	5,278	7,837	4,491	7,432
(1000's Euros)		(20,895)	(15,580)	(21,127)	(12,175)	(13,153)	(10,768)	(13,888)
Total Assets per worker		335	144	274	238	142	240	137
(1000's Euros)		(1,308)	(102)	(895)	(253)	(100)	(258)	(98)
Profit/loss		125	169	119	108	157	84	148
(1000's Euros)		(2,705)	(831)	(2,743)	(1,099)	(766)	(1,187)	(855)
Wages	453	613	1,069	634	600	982	514	922
(1000's Euros)	(3,317)	(1,131)	(1,442)	(1,106)	(981)	(1,188)	(919)	(1,227)
N	199,232	20,100	9,539	18,128	17,478	9,012	11,864	5,220

NOTE: The above table provides statistics averaged over years of interest. Clean 1 refers to merger of firm financial data without value added per worker or capital per worker outliers, observations with difference in firm employment larger than two are discarded. Clean 2 is basically Clean 1 with firms that hire more than 15 workers. Cont. denotes firm-year observations without any discontinuities.

Table A2: Basic characteristics of analysed sample, years 1997-2001

	Correlation		**AIDA match**	**Empl. difference**
Merger	No. employed	Wages	(% y-f obs.)	(no. obs)
Raw	0.86	0.34	90	-
Cleaned 1	0.96	0.32	91	108
Cleaned 2	0.96	0.95	96	124
Cleaned 1 + cont.	0.96	0.95	-	-
Cleaned 2 + cont.	0.96	0.95	-	-

NOTE: The column AIDA match displays the share of year-firm observations from AIDA dataset that were matched with VWH. Empl. difference is the number of obserations in the merged dataset where the difference in employment counts between VWH and AIDA exceeds 100 employees. Clean 1 refers to merger of firm financial data without value added per worker or capital per worker outliers, observations with difference in firm employment larger than two are discarded. Clean 2 is basically Clean 1 with firms that hire more than 15 workers. Cont. denotes firm-year observations without any discontinuities.

Table A3: Worker characteristics in the analysed sample, years 1997-2001

	Entire Sample						Entrants					
	VWH	Raw	Cleaned 1		Cleaned 2		VWH	Raw	Cleaned 1		Cleaned 2	
			all	cont.	all	cont.			all	cont.	all	cont.
Number of workers	10,251,807	663,375	593,541	353,433	492,135	269,068	1,120,026	62,368	56,841	33,745	45,522	24,483
Female	0.35	0.31	0.29	0.29	0.29	0.30	0.32	0.27	0.26	0.26	0.26	0.26
	(0.48)	(0.46)	(0.46)	(0.46)	(0.45)	(0.46)	(0.47)	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)
Age	34.3	33.9	34.0	33.8	34.3	34.2	31.9	30.9	30.8	30.9	30.9	30.9
	(10.4)	(10.0)	(10.0)	(10.0)	(10.1)	(10.1)	(10.1)	(9.2)	(9.2)	(9.3)	(9.2)	(9.3)
log(Wage), weekly	6.49	6.55	6.58	6.57	6.59	6.59	6.29	6.43	6.45	6.45	6.46	6.47
	(0.54)	(0.43)	(0.40)	(0.39)	(0.40)	(0.40)	(0.49)	(0.42)	(0.40)	(0.41)	(0.39)	(0.42)
Tenure (years)							1.24	1.46	1.51	1.50	1.51	1.50
							(1.45)	(1.31)	(1.34)	(1.29)	(1.33)	(1.27)
Job-to-job							0.45	0.57	0.58	0.58	0.60	0.60
							(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Linked							0.15	0.16	0.15	0.15	0.16	0.17
							(0.35)	(0.36)	(0.36)	(0.36)	(0.37)	(0.37)
Blue collar (%)	60.77	66.95	65.40	65.93	67.00	67.33	70.43	67.15	65.53	65.91	67.30	67.23
Office worker (%)	29.57	25.12	26.15	25.28	24.92	24.27	18.27	21.39	22.34	21.46	21.38	21.02
Director (%)	2.27	1.53	1.56	1.48	1.68	1.71	1.04	1.02	1.07	1.10	1.18	1.30

NOTE: Clean 1 refers to merger of firm financial data without value added per worker or capital per worker outliers, observations with difference in firm employment larger than two are discarded. Clean 2 is basically Clean 1 with firms that hire more than 15 workers. Cont. denotes firm-year observations without any discontinuities.

Figure A1: Linked hires and firm productivity

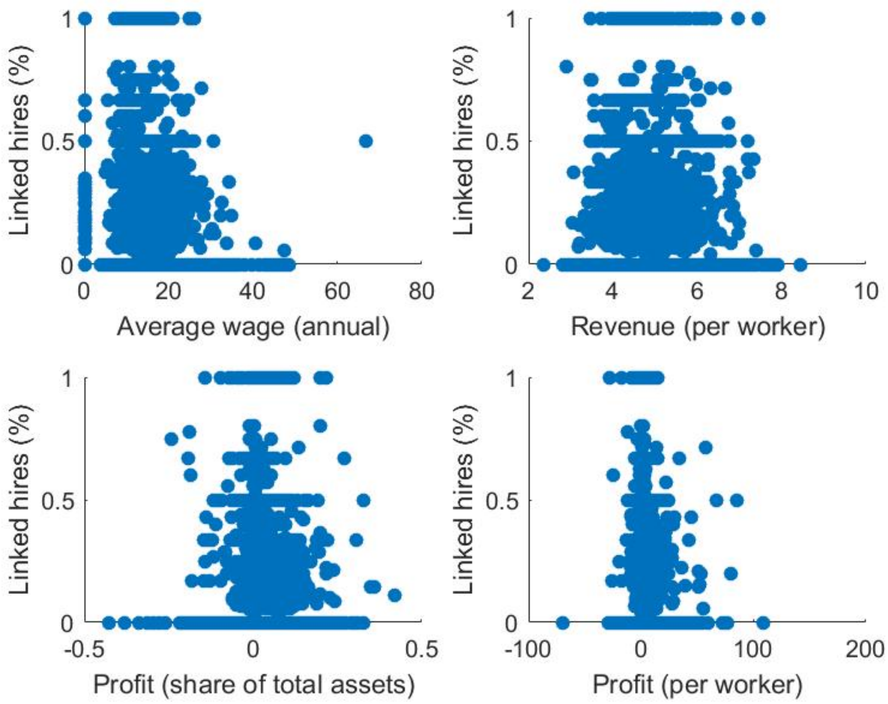
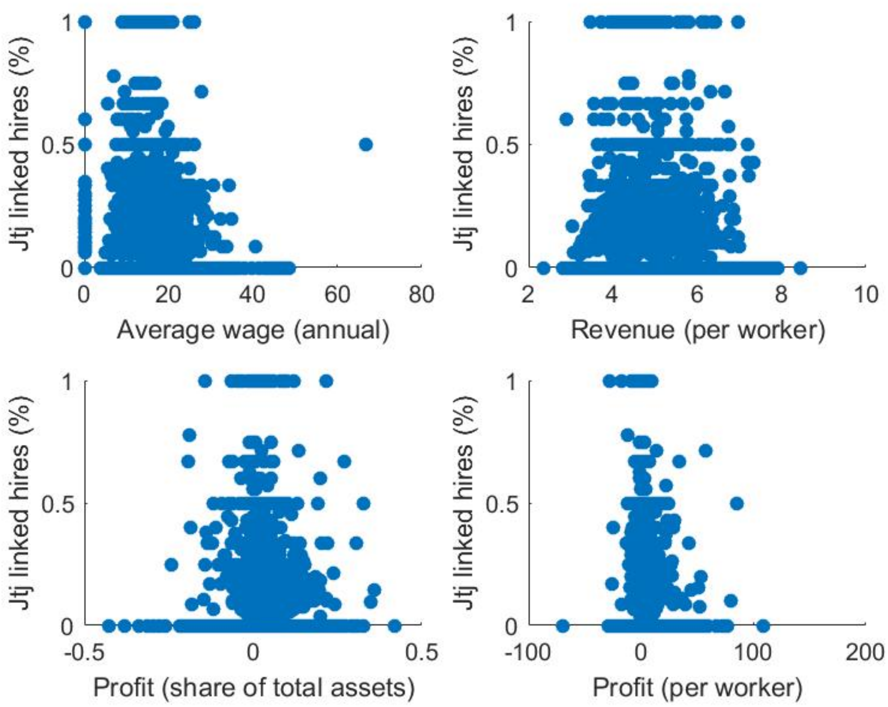


Figure A2: On-the-job linked hires and firm productivity



A.2.2 Industrial Districts

Table A4: Share of same industry and industrial cluster hires, 1995-2001

	Same industry		**Industrial cluster**	
Hires	1-digit	3-digit	1-digit	3-digit
All	61.47%	28.85%	77.90%	37.64%
Linked	66.32%	31.45%	77.24%	41.01%

NOTE: The above table provides statistics averaged over years of interest. Sample size includes $4,324$ firm-year observations.

Table A5: Basic characteristics of the sample of same-industry hires, years 1995-2001.

	Same Industry Hires					
	All		**Linked**		**Linked$\times$ Jtj**	
	Mean	SD	Mean	SD	Mean	SD
Age	32.1	9.92	33.7	9.79	33.8	9.36
Female	0.32	0.47	0.31	0.46	0.30	0.46
Wage (weekly)	6.40	0.39	6.45	0.41	6.53	0.38
Unempl. spell	8.44	15.47	6.71	13.97	-	-
Experience (years)	11.26	8.16	12.81	7.96	13.35	7.78
Industry Experience (1-digit)	6.51	6.71	7.97	7.09	8.73	7.21
Industry Experience (2-digit)	5.57	6.23	6.77	6.64	7.29	6.76
Industry Experience (3-digit)	4.69	5.96	5.80	6.45	6.27	6.64
Industry Experience (4-digit)	3.33	5.36	4.13	5.91	4.44	6.12
Linked	0.20	0.40	-	-	-	-

NOTE: The above table provides statistics for samples of different size: *All*: N = 94,736 (78,518 individuals), *Linked*: N = 18,799, *Linked* $\times$ *Jtj*: N = 12,058. Wages are in log, winsorized at 1^{st} and 99^{th} percentiles.

Table A6: Industrial Districts in Veneto, 1997-2001

Industrial District	SLL Code	Industry	Number of hires (share)					
			LLM		LLM × Industry		Within Ind. District	
			All	Linked	All	Linked	All	Linked
Arzignano	139	Leather, footwear	14,258 (5.07)	2,118 (5.48)	4,745 (1.69)	983 (2.54)	2,428 (51.17)	674 (14.20)
Bassano del Grappa	141	Wood, furniture	15,487 (5.51)	1,957 (5.07)	1,893 (0.67)	233 (0.60)	547 (28.90)	107 (5.65)
Schio	142	Metal products, machines, electronics	8,252 (2.94)	1,267 (3.28)	3,985 (1.42)	623 (1.61)	1,394 (34.98)	230 (5.77)
Thiene	143	Textiles, clothing	11,466 (4.08)	1,851 (4.79)	2,309 (0.82)	505 (1.31)	792 (34.30)	250 (10.83)
Vicenza	144	Jewelery, musical instruments, games, toys	26,797 (9.54)	3,579 (9.27)	6 (0.00)	-	-	-
Castelfranco Veneto	151	Textiles, clothing	16,621 (5.91)	2,225 (5.76)	2,357 (0.84)	363 (0.94)	917 (38.91)	204 (8.66)
Conegliano	152	Wood, furniture	28,456 (10.13)	3,416 (8.84)	4,072 (1.45)	554 (1.43)	792 (19.45)	188 (4.62)
Montebelluna	153	Wood, furniture	29,277 (10.42)	4,347 (11.25)	5,768 (2.05)	1,029 (2.66)	2,145 (37.19)	497 (8.62)
Pieve di Soligo	154	Wood, furniture	11,600 (4.13)	1,795 (4.65)	3,690 (1.31)	739 (1.91)	1,272 (34.47)	407 (11.03)
Total			162,214 (57.73%)	22,555 (58.39%)	28,825 (10.26%)	5,029 (13.00%)	10,287 (35.69%)	2,557 (8.83)
Links Statistics								
Linked hires			13.90%		17.45%		24.89%	
JtJ hires			53.36%		55.57%		61.89%	
Linked × Jtj hires			8.82%		11.55%		17.22%	

NOTE: The above table provides statistics averaged over years of interest. Sample size of All entrants $N = 281,209$, Linked entrants $N = 38,683$. Industrial Disticts are distinguished according to Istat classification (2011), that identifies 141 industrial areas on the basis of Local market areas (SLL in Italy) and the analysis of their economic specialization. The above tabel presents only the clusters that are located in Trevisa or Vicenza provinces. Share of hires in column (4) - (7) are computed with respect to total hires, respectively all and linked ones. Shares in columns (8) and (9) are set with respect to all hires in Industrial District for all and linked ones respectively.

A.3 Placebo Checks

Table A7: Placebo check - output and productivity analysis

Dep. var:	**Output**$_t$			**Productivity**$_t$		
Model:	OLS	OLS	IV	OLS	OLS	IV
$Non-Links_{t-1}$	-0.001	-0.002	-0.020	-0.008	0.006	-0.021
	(0.006)	(0.006)	(0.013)	(0.018)	(0.020)	(0.013)
$Links_{t-1}$	0.058**	0.026	0.031**	0.048	0.033	0.027**
	(0.026)	(0.031)	(0.013)	(0.033)	(0.035)	(0.013)
$Hires_{t-1}$	0.012**	0.028***	0.042***	0.021	0.023	0.042***
	(0.006)	(0.011)	(0.014)	(0.018)	(0.018)	(0.014)
$Links_{t-1} \times Hires_{t-1}$	-0.019**	-0.006	-0.015*	-0.015	-0.007	-0.012
	(0.009)	(0.012)	(0.008)	(0.011)	(0.012)	(0.008)
$Non-Links_{t-1} \times Hires_{t-1}$		-0.008*			-0.008	
		(0.004)			(0.005)	
$log(K_t)$	0.124***	0.125***	0.134***			
	(0.019)	(0.019)	(0.020)			
$log(L_t)$	0.224***	0.226***	0.0222***			
	(0.026)	(0.026)	(0.023)			
$log(M_t)$	0.385***	0.385***	0.381***			
	(0.014)	(0.014)	(0.014)			
R^2	0.986	0.986	0.986	0.974	0.975	0.933

Table A8: Placebo check - number of non-referred workers, Output

Dep. var: $log(Output)_{ijst}$	**Baseline**	**Olley - Pakes**	**IV**
$Non - Referred$	-0.008	0.046	0.036
	(0.015)	(0.037)	(0.028)
$log(Hires)$	0.04***	-0.02	0.38*
	(0.013)	(0.035)	(0.019)
$Non - Referred \times log(Hires)$	-0.01**	-0.01	-0.025
	(0.005)	(0.010)	(0.017)
$log(K)$	0.13***	0.07	0.13**
	(0.019)	(0.094)	(0.061)
$log(L)$	0.22***	0.15***	0.22***
	(0.023)	(0.029)	(0.049)
$log(M)$	0.39***	0.29***	0.38***
	(0.014)	(0.029)	(0.066)
R^2	0.98		0.98
N	4,325	1,714	4,307

Table A9: Placebo check - output and productivity analysis

Dep. var:	**Output**$_t$		**Productivity**$_t$	
	(1)	(2)	(3)	(4)
Connected hires (%)	0.018***	0.018***	0.025***	0.025***
	(0.007)	(0.007)	(0.008)	(0.008)
$Hires_{t-1}$		0.003		-0.001
		(0.06)		(0.007)
$log(K_t)$	0.016	0.015		
	(0.025)	(0.025)		
$log(M_t)$	0.303***	0.303***		
	(0.018)	(0.018)		
R^2	0.957	0.957	0.946	0.946

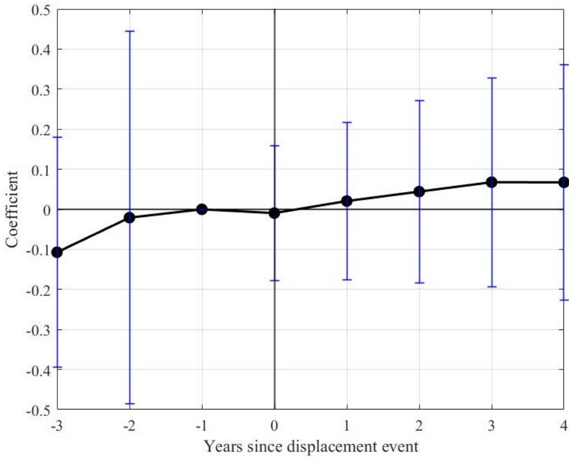
NOTE: Size of the sample $N = 4,325$. *Connected hires* is a percentage of linked entrants as a share of all hires. The model includes differences of input factors, referrals, hires, their interaction, LLM-year and industry-year fixed effects. Remaining models include all of the aforementioned fixed effects as well as production inputs (in Output) and firm fixed effects. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Table A10: Impact of number of connected hires on firms' productivity and output - PLACEBO event study.

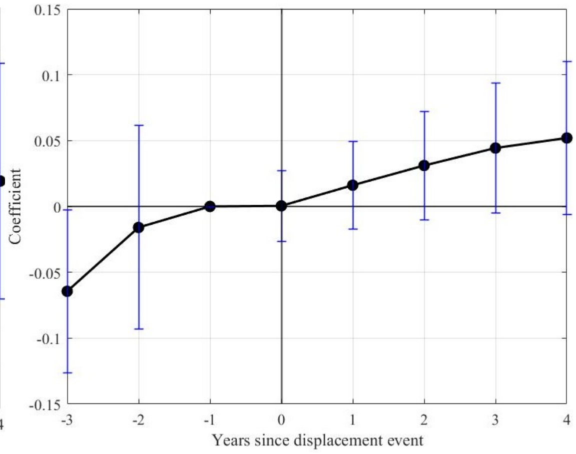
Panel A: **Productivity**			
Event:	$\tau \in [0,1]$	$\tau \in [2,3]$	$\tau \in [0,3]$
Non-Connected Hire	0.006	0.056	0.031
	(0.093)	(0.123)	(0.108)
Non-Connected Hire Shock	0.043	0 .059	0.051
	(0.028)	(0.038)	(0.031)
Panel B: **Output**			
Event:	$\tau \in [0,1]$	$\tau \in [2,3]$	$\tau \in [0,3]$
Non-Connected Hire	0.008	0.038	0.023
	(0.015)	(0.023)	(0.019)
Non-Connected Hire Shock	0.012**	0.018**	0.015**
	(0.006)	(0.007)	(0.006)

NOTE: Note: Estimates taken from specification of form given in Equation (1.4) where the dependent variable is the number of patents applications. The sample size is $4,380$ ($1,275$ firms), it includes ony firms with at least one year after the event. Sample includes only firms with more than 2 observations. The model includes year and firm fixed effects, industry trends and LLM trends, network size, number of hired workers, firm size, average wage and firm age. Numbers in parentheses are standard errors clustered at the LLM level. $\tau = [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Figure A3: Firms' Productivity and Output, Relative to Year of a Connected Worker Displacement - PLACEBO Event Study (Non-Connected Hire)



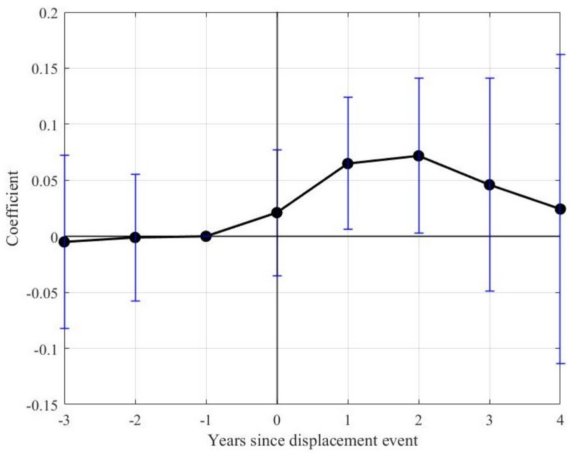
(a) Productivity



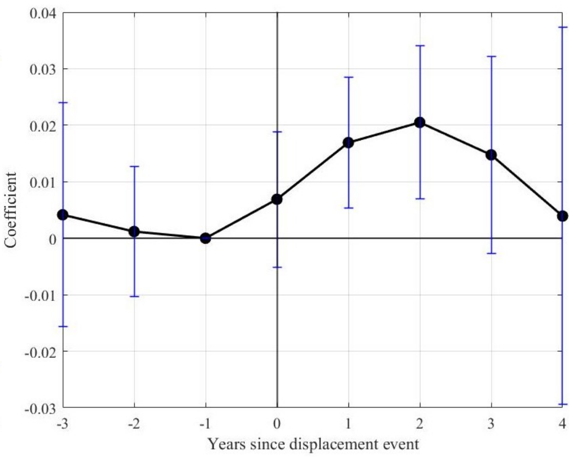
(b) Output

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. Sample includes only firms with at least one observation following the event. The bands around the point estimates are 95 percent robust confidence intervals.

Figure A4: Firms' Productivity and Output, Relative to Year of a Connected Worker Displacement - PLACEBO Event Study (Non-Connected Hire Shock)



(a) Productivity



(b) Output

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. Sample includes only firms with at least one observation following the event. The bands around the point estimates are 95 percent robust confidence intervals.

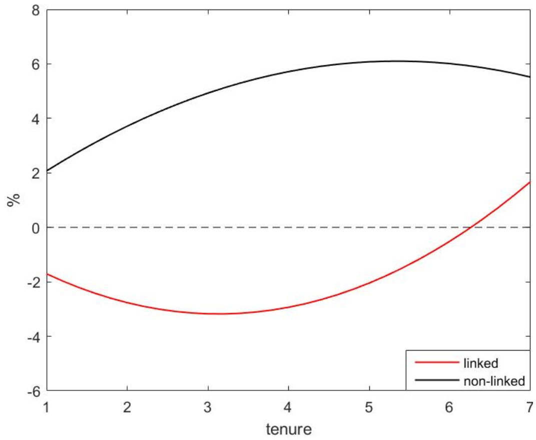
A.4 Referral Heterogeneity

Entry wage. The panel structure of VWH data allows to distinguish the firm entry stage of workers as well as track them throughout whole job tenure and examine performance while facing exogenous employment shocks such as firm closure (if occurs). In fact, the analysis proves the advantage of job-to-job linked entrants while employed and higher employment probability given firm closures. In the co-worker link literature (HS), linked firm entrants have initial wage advantage of 3.6%. Table 1.3 presents the results of entry wage regression with firm and industry-year fixed effects. The basic specification shown in column (1) is fairly close to results of Swedish authors. Distinguishing short and long unemployment spell and their interaction with links, column (4) allows to gauge the decreasing advantage of linked and non-linked entrants.[3] Linked employees who experienced long unemployment spell are those who potentially used informal contacts in order to exit unemployment spell as it lengthened. Social network served as the insurance against unemployment spell. Interpreting column (4) one has to remember that the reference group in this case are non-linked entrants with long unemployment spell.

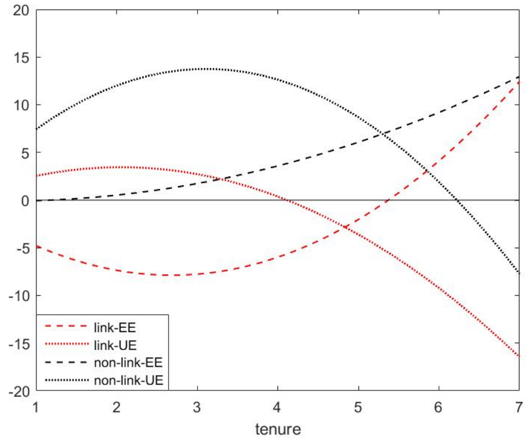
Surprisingly, in none of the specifications the number of links among incumbents in the destination firm has any impact on the entry wage. It seems that the size of the network (proxied by variable *Nr links*) doesn't matter for the entry wage. What matters is the fact of being linked or type of employment transition. One of the concerns while measuring the impact of unemployment spell of the linked worker on entry wage is that in above analysis the only requirement for the incumbent is to be employed in the destination firm at least 3 weeks before the transition. It does not measure if our link was already employed in the firm when we entered unemployment. Taking that into account may allow to identify workers who use referrals as insurance and contact their links only when the unemployment spell lengthens. Appendix A.5 corrects for that and finds significant negative effect for linked workers with long unemployment spell. Brief description of the exercise and results are shown in Table A12.

Returns to tenure. For the purpose of investigating the returns to tenure and spell length among referred workers, I track the job spells of the entrants and construct panel of wage profiles. Recall that the raw data suggests the convergence of linked and job-to-job linked workers to non-linked and job-to-job employees respectively. I use returns to tenure framework, introduced by Altonji and Shakotko (1985), Panel (b) of Figure A5 plots the results. As expected, linked workers have lower returns to employer than non-linked ones. Distinguishing further job-to-job transition, Figure A5b displays returns to employer for 4 considered groups. The baseline group are non-linked workers who experienced unemployment spell longer than three weeks. The wage evolution between

[3] Short unemployment spells last between 3 weeks and median unemployment spell - 11 weeks, long spells denote those above 11 weeks.



(a) Wage profile, returns to employer



(b) Wage profile, returns to employer

Figure A5: Wage characteristics of entrants, years 1995 - 2001

job-to-job and non-jtj hires seems similar - explaining convergence observed in the raw data.

Turnover. The advantage of job-to-job linked workers once again appears in the tenure duration analysis. Panel B of Table 1.3 reports the results of Proporitional Hazard model. In line with previous literature referred workers have longer tenures, job-to-job linked ones have additional advantage in job spells (Table 1.3 column (2)).[4] Interestingly, high number of former co-workers in the destination firm induces longer tenure, sign of a peer pressure of the network.

Firm closure. The remaining part of the referral heterogeneity analysis focuses on the exogenous employment shocks. Both Cingano and Rosolia (2012) and Glitz (2017) find that the network quality (defined as share of employed in one's network) reduces unemployment duration after firm closure. The main idea of the following exercise is that network employment rate is not the only thing that matters during unemployment spell, linked workers may perform better during mass reductions as they are potentially more skilled workers. For that purpose I construct indicator variable for unemployment spells no longer than 26 weeks.[5] To prove the robustness of effect for linked workers, Table A11 includes network employment rate and instrumental variable from previous literature. The IV for employment rate is a percentage of former co-workers hit by exogenous mass-layoffs, constructed as in Glitz (2017). The variables *Connected* and *Jtj* in Table A11 denote workers who originally were connected or transitioned job-to-job. Given column (1) it becomes clear that linked and job-to-job linked workers have higher probability of exiting unemployment before 26 weeks. The results are not disturbed by introduction of network employment rate (column (3)). The interaction term in column

[4]E.g. Brown et al. (2016) or Dustmann et al. (2016) report lower turnover of referred workers

[5]Considered unemployment spells are shorter than those in Glitz (2017), however given the distribution of the unemployment duration such specification makes more sense.

Table A11: Firm closure - employment probability

Dep variable:	OLS				IV
Empl. proba.	(1)	(2)	(3)	(4)	(5)
Connected	0.021**	0.017*	0.020**	-0.091**	0.018
	(0.008)	(0.009)	(0.008)	(0.044)	(0.078)
Empl. rate			0.050***	0.033*	0.181**
			(0.018)	(0.019)	(0.084)
Empl. rate × *Connected*				0.129***	0.001
				(0.051)	(0.090)
Jtj	0.044***	0.029***	0.044***	0.044***	0.042***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Jtj × *Connected*	-0.014	-0.009	-0.014	-0.019	-0.013
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
Firm f.e.	-	+	-	-	-

NOTE: Size of the sample N = 14,237. IV model uses co-worker network employment rate defined as in *Glitz (2017)*. Control variables include age, age^2, gender, residence and position on the worker side; province, size, urban area on the firm side and *Industry* × *time* and *Firm* fixed effects. *Empl. rate* variable defined as in *Cignano and Rosolia(2012)*. IV model uses instrument for *Empl. rate* defined as in *Glitz (2017)*. $*p < 0.1$,$** \ p < 0.05$,$*** \ p < 0.01$.

(4) changes the sign of *Connected* variable, offseted by the former for high values of network employment rates. In instrumental variable regression linked workers are no longer privileged facing firm closure, former job-to-job entrants remain their advantage. The IV analysis confirms the results of Glitz (2017) in terms of sign and significance of the coefficient, the difference in volume may resolve from the different sample or *Empl. proba.* variable specification.

A.5 Unemployment duration dependence

Link employment at the beginning of entrant's unemployment spell.

One of possible extensions includes distinguishing entrants who use referrals as insurance against the unemployment. For that purpose I distinguish referred entrants whose links were employed at the entry firm in the starting week of unemployment spell. If any of former co-workers of worker already have worked at the destination firm when he became unemployed and the unemployed worker still experiences long unemployment spell, he might have contacted his link only to exit the spell. He used the relationship as the unemployment spell lengthened, not as an opportunity for better-paid job. Variable *Provider empl.* takes value 1 if any of the links were employed at the future firm when entrant started his unemployment spell prior to hire. Intuitively one should observe decline in entry wage for those with *Provider empl.* equal to one and long unemployment spell.

As expected, long unemployed workers whose links worked at entry firm at the beginning of unempl. spell have significantly lower wages (see Panel A.). If instead of unemployment duration one uses indicators of short and long spells, similar effect can be seen only for the former. Interpreting variable *Provider empl.* is pointless, as for instance in Panel A. it captures partly the effect of job-to-job transitions.

Table A12: Entry wage regression, referred workers, years 1995-200

Dep variable: $log(w_{ij}^{E})$	(1)	(2)	(3)
		Panel A	
Provider empl.	-0.002	0.035***	0.035***
	(0.007)	(0.009)	(0.009)
Unempl. duration	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Provider empl. $\times$ *Unempl. dur.*		-0.002***	-0.002***
		(0.000)	(0.000)
R^2	0.69	0.69	0.69
		Panel B	
Provider empl.	-0.003	0.029	0.026
	(0.006)	(0.028)	(0.028)
Jtj	0.103***	0.079***	0.081***
	(0.005)	(0.027)	(0.027)
Short spell	0.036***	0.074***	0.074***
	(0.006)	(0.013)	(0.013)
Short spell $\times$ *Provider empl.*		-0.067**	-0.063**
		(0.030)	(0.030)
Long spell $\times$ *Provider empl.*		-0.019	-0.017
		(0.028)	(0.028)
R^2	0.69	0.68	0.69
Firm f.e.	+	+	+
Industry $\times$ *year f.e.*	-	-	+

NOTE: Sample is of the size: n = 38,683. Control variables contain age, age^2, gender, residence, position on the worker side; province, size, firm and industry-year fixed effects. Variable *Provider empl.* denotes whether any of the links were employed at the entry firm when entrant stared his unemployment spell. Dep. variable $log(w_{ij}^{E})$is winsorized at 1^{st} and 99^{th} percentiles. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

A.6 Robustness checks

Table A13: Entry wage regression, years 1995-2001

	(1)	(2)	(3)	(4)	(5)	(6)
A. All entrants						
Connected	0.029***	0.026***	0.028***	0.052**	0.026***	0.051**
	(0.002)	(0.003)	(0.002)	(0.025)	(0.003)	(0.025)
Nr links	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Jtj	0.094***	0.094***	0.114***	0.114***	0.094***	0.114***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Jtj × *Connected*		-0.002		-0.027	-0.002	-0.026
		(0.003)		(0.025)	(0.003)	(0.025)
Short spell			0.044***	0.044***		0.044***
			(0.002)	(0.002)		(0.002)
Short spell × *Connected*				-0.029		-0.027
				(0.025)		(0.025)
Office worker	0.257***	0.254***	0.257***	0.253***	0.254***	0.254***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
Director	0.839***	0.849***	0.838***	0.848***	0.849***	0.849***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Office worker × *Connected*		0.025***		0.025***	0.025***	0.024***
		(0.004)		(0.004)	(0.004)	(0.004)
Director × *Connected*		-0.060***		-0.059***	-0.062***	-0.061***
		(0.016)		(0.016)	(0.016)	(0.016)
R^2	0.58	0.58	0.58	0.58	0.58	0.58
Firm f.e.	+	+	+	+	+	+
Industry × *year f.e.*	-	-	-	-	+	+
B. Connected entrants						
Nr links	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Jtj	0.085***	0.102***	0.085***	0.102***	0.071***	0.115***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.011)	(0.015)
Short spell		0.035***		0.035***		0.082***
		(0.005)		(0.005)		(0.018)
R^2	0.69	0.69	0.69	0.69	0.81	0.81
Firm f.e.	+	+	+	+	+	+
Industry × *year f.e.*	-	-	+	+	+	+
Sample	*All*	*All*	*All*	*All*	*Position*	*Position*

NOTE: Samples are of the size: *All entrants* - n = 281,209; *Connected entrants* - n = 38,683; *Connected entrants with higher position* - n = 6,550. Control variables contain age, age^2, gender, residence on the worker size; province, size, firm and industry-year fixed effects. Columns (4) and (6) include additionally interaction term *Long spell* × *Link* for identification purposes. Dep. variable $log(w_{ij}^E)$ is winsorized at 1^{st} and 99^{th} percentiles. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Entry wage of entrants, robustness check, years 1995-2001

Dep. variable: $log(w_{ij}^E)$	Men		Manufacturing, services		Office worker, director		Tenure $\geq$ 49 weeks	
Connected	0.031***	0.032***	0.030***	0.028***	0.018***	0.014*	0.024***	0.025***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.008)	(0.002)	(0.003)
Nr links	0.000*	0.000*	0.000	0.000	-0.000*	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Jtj	0.098***	0.098***	0.102***	0.102***	0.086***	0.085***	0.073***	0.074***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
Jtj $\times$ *Connected*		-0.004		-0.002		0.008		-0.010**
		(0.004)		(0.004)		(0.009)		(0.004)
Office worker	0.309***	0.306***	0.280***	0.276***			0.237***	0.232***
	(0.002)	(0.002)	(0.002)	(0.002)			(0.002)	(0.002)
Director	0.844***	0.856***	0.857***	0.868***	0.410***	0.418***	0.790***	0.798***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)
Office worker $\times$ *Connected*		0.020***		0.028***				0.039***
		(0.006)		(0.005)				(0.005)
Director $\times$ *Connected*		-0.073***		-0.063***		-0.048***		-0.050***
		(0.002)		(0.018)		(0.017)		(0.016)
R^2	0.60	0.60	0.59	0.59	0.71	0.71	0.69	0.69
N	193,562	193,562	207,248	207,248	54,065	54,065	140,894	140,894

NOTE: Sample containing entrants with entry job tenure greater or equal to 49 was chosen arbitrary, as median job duration is 49. Control variables contain age, age^2, gender, residence on the worker side; province and employment size on the firm side and firm fixed effects. Dep. variable $log(w_{ij}^E)$.*$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Cox Proportional Hazard Model, robustness check

Dep variable: $Tenure_i$	Men		Manufacturing, services		Office worker, director		Tenure > 49 weeks	
Connected	0.88***	0.89***	0.85***	0.86***	0.88***	0.88*	0.11***	0.19***
	(0.017)	(0.025)	(0.016)	(0.025)	(0.034)	(0.062)	(0.017)	(0.044)
Jtj	0.61***	0.61***	0.64***	0.64***	0.87***	0.87***	1.26***	1.28***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.020)	(0.021)	(0.053)	(0.055)
Jtj $\times$ *Connected*		0.96		0.98		0.99		0.48**
		(0.036)		(0.037)		(0.080)		(0.138)
Office worker	0.96***	0.96***	0.97***	0.97***			1.29***	1.29***
	(0.017)	(0.018)	(0.016)	(0.016)			(0.060)	(0.060)
Director	0.84***	0.84***	0.81***	0.81***	0.79***	0.79***	1.19	1.19
	(0.048)	(0.048)	(0.049)	(0.049)	(0.046)	(0.046)	(0.175)	(0.174)
N	193,562	193,562	207,248	207,248	54,065	54,065	140,894	140,894

NOTE: Sample containing entrants with entry job tenure greater or equal to 49 was chosen arbitrary, as median job duration is 49. Control variables include age, age^2, gender, residence on the worker side; province, size, urban area, industry on the firm side. Proportional Hazard model is right censored. Job tenure is measured in weeks. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Table A16: Referral probability, logit

Dep variable: $Pr(Connected_i = 1)$	Whole		Manufacturing, services		Men		Office worker, director	
Age	0.072***	0.046***	0.075***	0.046***	0.068***	0.041***	0.128***	0.093***
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
Age × Jtj		0.028***		0.030***		0.025***		0.034***
Age^2 × Jtj		-0.001***		-0.001***		-0.001***		-0.001***
Blue collar	0.431***	0.390***	0.425***	0.375***	0.432***	0.382***		
Office worker	0.147***	0.058**	0.113***	0.016***	0.282***	0.185***		
Director	0.080	-0.020	0.146**	0.038	0.092	-0.019	-0.220***	-0.229***
Size	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
N	281,209	281,209	207,248	207,248	193,562	193,562	54,065	54,065

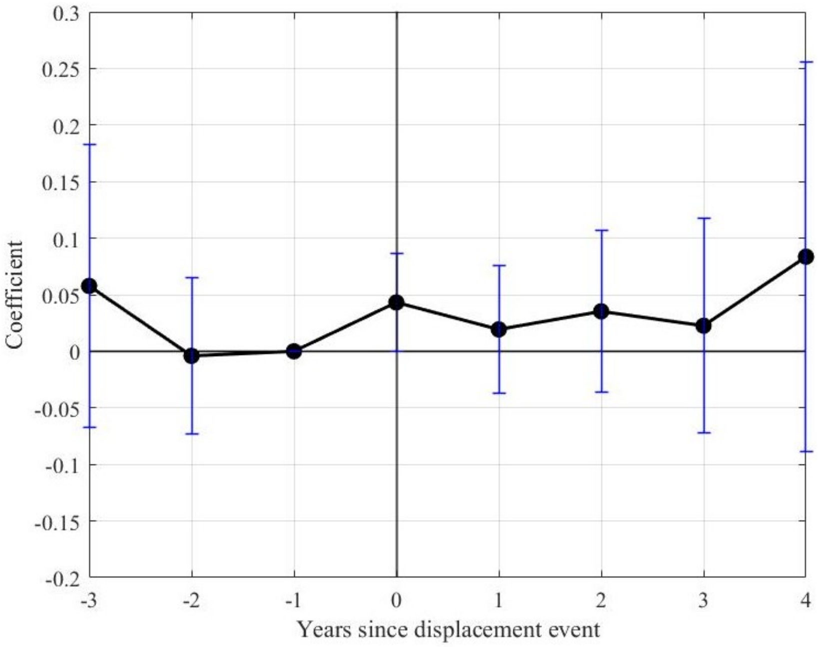
NOTE:Control variables include gender, position, province of residence from worker side; urban area, province and industry from the firm side as well as time fixed effects. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Firm closure - unemployment duration and future referral probability

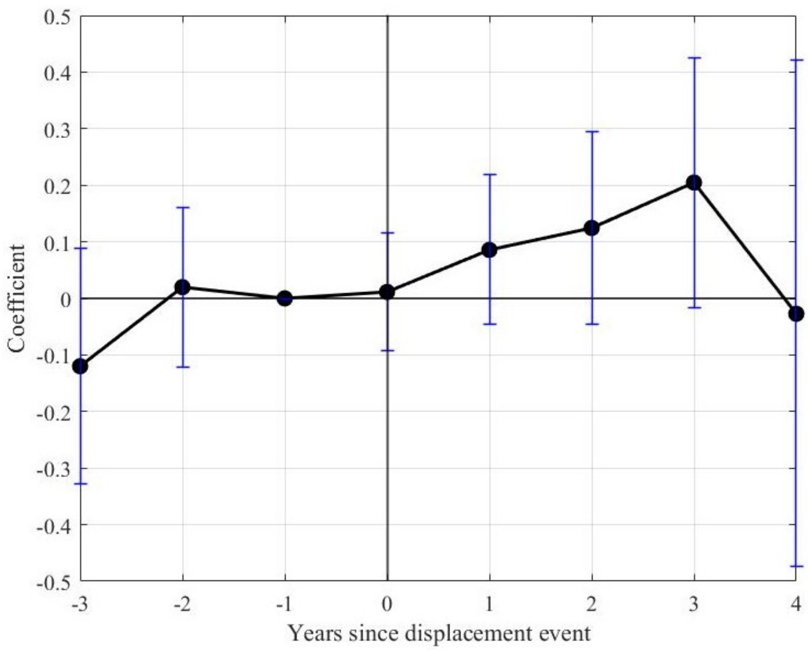
Dep variable:	**Duration**			**Future referral**		
Empl. proba.	(1)	(2)	(3)	(4)	(5)	(6)
Connected	1.09**	1.09**	0.74	0.019*	0.019*	0.044
	(0.039)	(0.039)	(0.143)	(0.011)	(0.011)	(0.058)
Empl. rate		1.59***	1.49***		-0.058**	-0.055**
		(0.122)	(0.122)		(0.024)	(0.026)
Empl. rate × Connected			1.57			-0.029
			(0.344)			(0.067)
Jtj	1.23***	1.22***	1.22***	-0.013***	-0.012**	-0.012**
	(0.024)	(0.024)	(0.024)	(0.006)	(0.006)	(0.006)
Jtj × Connected	0.97	0.96	0.95	0.004	0.005	0.006
	(0.044)	(0.044)	(0.043)	(0.014)	(0.014)	(0.014)

NOTE: Size of the sample N = 14,237. Duration analysis uses uncensored Proportional Hazard model. Future referral uses OLS. Control variables include age, age^2, gender, residence and position on the worker side; province, size, urban area, industry and local labor market on the firm side. Variable *Empl. rate* is a fraction of former co-workers employed in the week of job loss. Unemployment spell is measured in weeks. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Figure A6: The effect of network displacements on connected and market inventor hires -event study



(a) Connected Hires



(b) Market Hires

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent robust confidence intervals.

Table A18: Robustness check - additional controls

Dep. var:	$ln(Output)_{ijst}$				$lnTFP_{ojst}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Connected_{t-1}$	0.057**	0.058**	0.057**	0.060**	0.057**	0.058**	0.058**	0.060**
	(0.026)	(0.026)	(0.026)	(0.028)	(0.026)	(0.026)	(0.026)	(0.028)
$Connected_{t-2}$				0.037*				0.041*
				(0.022)				(0.022)
$Connected_{t-3}$				-0.044				-0.025
				(0.035)				(0.036)
$Connected_{t-4}$				-0.009				0.001
				(0.071)				(0.071)
$log(Hires)$	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**	0.014**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
$Connected \times log(Hires)$	-0.019**	-0.019**	-0.019**	-0.021**	-0.018*	-0.018*	-0.018*	-0.020*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$log(K)$	0.12***	0.12***	0.12***	0.12***				
	(0.020)	(0.020)	(0.020)	(0.020)				
$log(L)$	0.22***	0.22***	0.22***	0.022***				
	(0.024)	(0.024)	(0.024)	(0.023)				
$log(M)$	0.39***	0.39***	0.39***	0.039***				
	(0.014)	(0.014)	(0.014)	(0.014)				
Avg_age	+	+	+	+	+	+	+	+
$Female\_share$	+	+	+	+	+	+	+	+
$Position\_share$		+	+	+		+	+	+
$Part\_time\_share$			+	+			+	+
R^2	0.98	0.98	0.98	0.98	0.93	0.93	0.93	0.93
N	4,325	4,325	4,325	4,325	4,325	4,325	4,325	4,325

Table A19: Extension - Firm Closure IV

Dep. var:	Output$_t$		Productivity$_t$	
	(1)	(2)	(3)	(4)
Connected hires	0.013*	0.013*	0.013*	0.012*
	(0.007)	(0.007)	(0.008)	(0.007)
$Hires_{t-1}$	0.014***	0.013***	0.016**	0.014**
	(0.005)	(0.005)	(0.005)	(0.005)
Avg wage		0.005***		0.004***
		(0.001)		(0.001)
$log(K_t)$	0.143***	0.131***		
	(0.020)	(0.020)		
$log(L_t)$	0.179***	0.218***		
	(0.022)	(0.023)		
$log(M_t)$	0.386***	0.382***		
	(0.014)	(0.014)		
R^2	0.986	0.986	0.932	0.933

NOTE: Size of the sample $N = 4,325$. *Connected hires* is a log number of linked entrants. The model includes differences of input factors, referrals, hires, their interaction, LLM-year and industry-year fixed effects. Remaining models include all of the aforementioned fixed effects as well as production inputs (in Output) and firm fixed effects. $*p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Table A20: Robustness check - good firms and annual hires

Dep. var.:	$log(Output)_{ijst}$			$logTFP_{ijst}$		
	Top 75% f.e.	Top 25% f.e.	Annual hires	Top 75% f.e.	Top 25% f.e.	Annual hires
Connected	0.065***	0.059**	0.113***	0.070***	0.070**	0.109***
	(0.007)	(0.039)	(0.003)	(0.007)	(0.025)	(0.004)
Hires	0.008	0.009	0.029***	0.010*	0.015	0.031***
	(0.121)	(0.285)	(0.002)	(0.093)	(0.134)	(0.001)
Connected × *Hires*	-0.021**	-0.015	-0.037***	-0.022**	-0.023**	-0.034**
	(0.017)	(0.117)	(0.008)	(0.019)	(0.033)	(0.014)
log(K)	0.020	-0.003	0.122***			
	(0.375)	(0.934)	(0.000)			
log(L)	0.163***	0.140***	0.184**			
	(0.000)	(0.003)	(0.000)			
log(M)	0.565***	0.619***	0.396***			
	(0.000)	(0.000)	(0.000)			
Observations	3,244	1,082	2,419	3,244	1,082	2,419
R^2	0.99	0.99	0.99	0.98	0.99	0.99

Table A21: Robustness check - impact on Output and productivity by groups. Matched employer-employee data, 1997-2001.

	Non-Agric. Sectors	Empl. > 15	Female % < 0.4	Old firms > 7 y.	Non urban	Blur-collar > 50 %
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Output			
Connected	0.057**	0.057**	0.076**	0.070**	0.050*	0.057**
	(0.029)	(0.023)	(0.017)	(0.016)	(0.060)	(0.040)
Hires	0.013**	0.009*	0.008	0.012**	0.013**	0.013**
	(0.012)	(0.078)	(0.204)	(0.040)	(0.010)	(0.017)
Connected × *Hires*	-0.019**	-0.018*	-0.024**	-0.025**	-0.017*	-0.020**
	(0.047)	(0.058)	(0.045)	(0.016)	(0.088)	(0.046)
R^2	0.99	0.99	0.99	0.99	0.99	0.99
log(K)	0.121***	0.114***	0.083***	0.118***	0.124***	0.067***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
log(L)	0.222***	0.194***	0.190***	0.236***	0.220***	0.204***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(M)	0.386***	0.367***	0.478***	0.393***	0.379***	0.416***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Panel B. Productivity			
Connected	0.057**	0.055**	0.086***	0.073**	0.049*	0.056**
	(0.033)	(0.027)	(0.009)	(0.014)	(0.065)	(0.046)
Hires	0.014***	0.009*	0.012*	0.014**	0.014***	0.014**
	(0.007)	(0.079)	(0.070)	(0.022)	(0.006)	(0.012)
Connected × *Hires*	-0.018*	-0.016*	-0.026**	-0.025**	-0.016	-0.020*
	(0.071)	(0.077)	(0.033)	(0.019)	(0.116)	(0.057)
Avg. wage	0.004***	0.005***	0.004***	0.004***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
R^2	0.97	0.98	0.97	0.98	0.97	0.97
Observations	4194	3596	3102	3233	3991	3353

Table A22: IV Estimates of the Effect of Connected Hires on Productivity

	Productivity		**Output**	
Dependent Variable	(1)	(2)	(3)	(4)
	Panel A: **2SLS Estimates**			
Connected Hire	0.143***	0.151***	0.037***	0.037***
	(0.042)	(0.042)	(0.010)	(0.010)
F-stat, 1st stage	225.37	215.74	226.77	215.97
N	4,647	4,647	4,647	4,647
Firm Characteristics	+	+	+	+
Industry and Time Trends	-	+	-	+
	Panel B: **First stage estimates**			
Displ. Workers$^{conn.}$	0.254***	0.246***	0.253***	0.246***
	(0.017)	(0.017)	(0.017)	(0.017)
	Panel C: **Reduced form estimates**			
Displ. Workers$^{conn.}$	0.036***	0.037***	0.009***	0.009***
	(0.011)	(0.010)	(0.003)	(0.002)

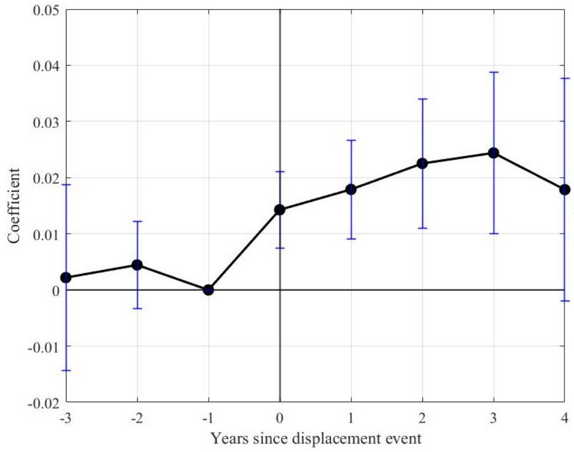
NOTE: Estimates taken from specification of form given in Equation (1.4) where the dependent variable is firm productivity (col. (1)-(2)) or firm output (col. (3)-(4)). Final sample includes only plants with more than 2 observations in the period of interest. Numbers in parentheses are a robust standard errors. Network size, firm and time fixed effects always included. *Firm Characteristics* : employment, network size, age, average wage. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Table A23: Impact of number of connected hires on firms' productivity and output - event study.

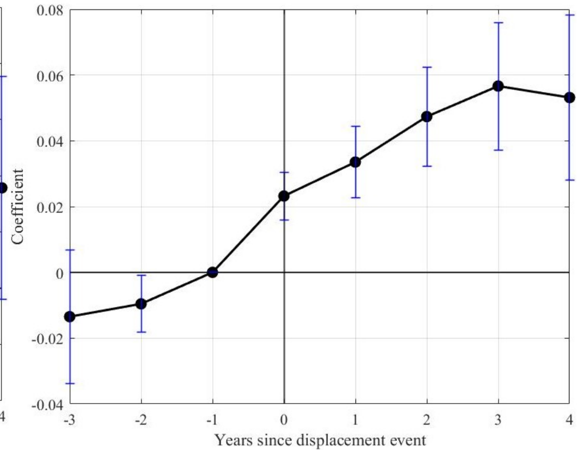
Panel A: **Productivity**			
Event:	$\tau \in [0,1]$	$\tau \in [2,3]$	$\tau \in [0,3]$
Baseline	0.035***	0.033*	0.034**
	(0.012)	(0.019)	(0.015)
Connected Hire Shock	0.092***	0.098**	0.095***
	(0.033)	(0.043)	(0.037)
Connected Worker Displacement	0.103***	0.194***	0.149***
	(0.021)	(0.043)	(0.032)
Panel B: **Output**			
Event:	$\tau \in [0,1]$	$\tau \in [2,3]$	$\tau \in [0,3]$
Baseline	0.016***	0.019***	0.018***
	(0.004)	(0.007)	(0.006)
Connected Hire Shock	0.020***	0.022**	0.021***
	(0.007)	(0.009)	(0.008)
Connected Worker Displacement	0.032***	0.059***	0.046***
	(0.005)	(0.010)	(0.007)

NOTE: Note: Estimates taken from specification of form given in Equation (1.4) where the dependent variable is the number of patents applications. The sample size is $4,380$ ($1,275$ firms), it includes ony firms with at least one year after the event. Sample includes only firms with more than 2 observations. The model includes year and firm fixed effects, industry trends and LLM trends, network size, number of hired workers, firm size, average wage and firm age. Numbers in parentheses are standard errors clustered at the LLM level. $\tau = [a,b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Figure A7: Firms' Output, Relative to Year of a Connected Hire and Connected Worker Displacement



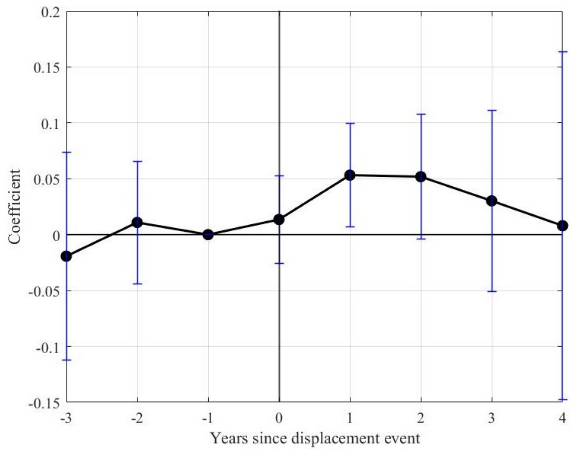
(a) Baseline



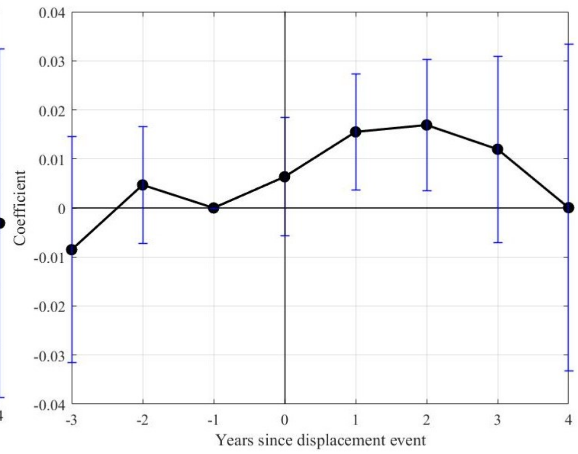
(b) Connected Worker Displacement

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent robust confidence intervals.

Figure A8: Firms' Productivity and Output, Relative to Year of a Connected Hire Shock



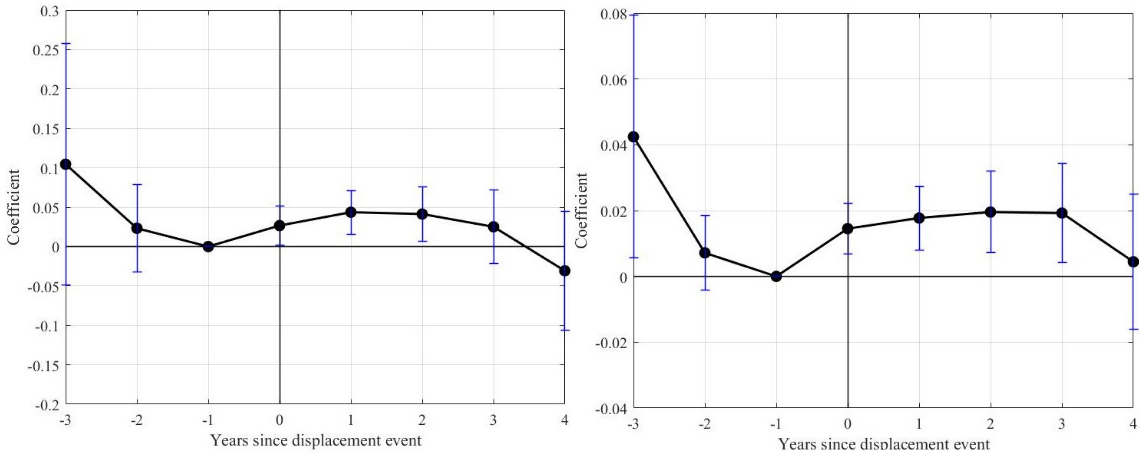
(a) Productivity



(b) Output

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent robust confidence intervals.

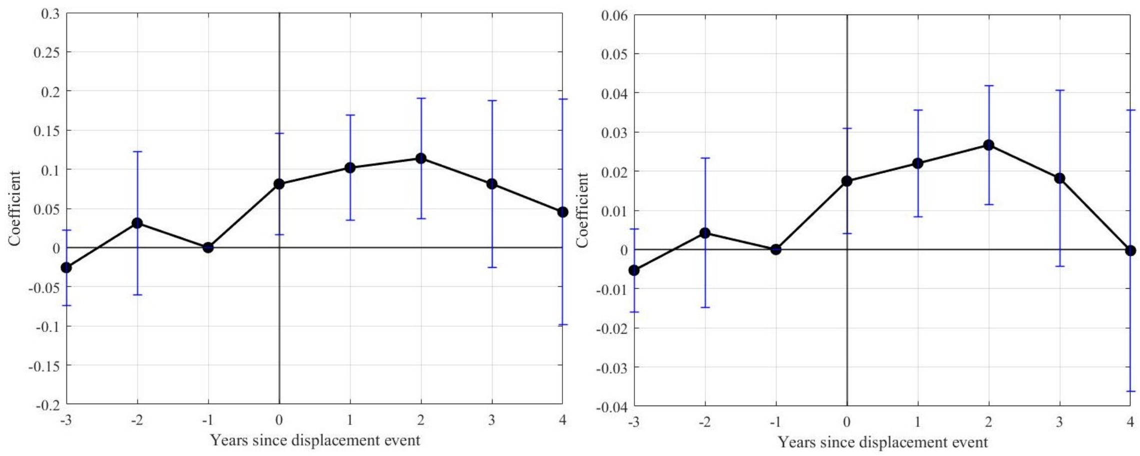
Figure A9: Firms' Productivity and Output, Relative to Year of a Connected Hire - Limited Sample



(a) Productivity (b) Output

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. Sample includes only firms with at least one observation following the event. The bands around the point estimates are 95 percent robust confidence intervals.

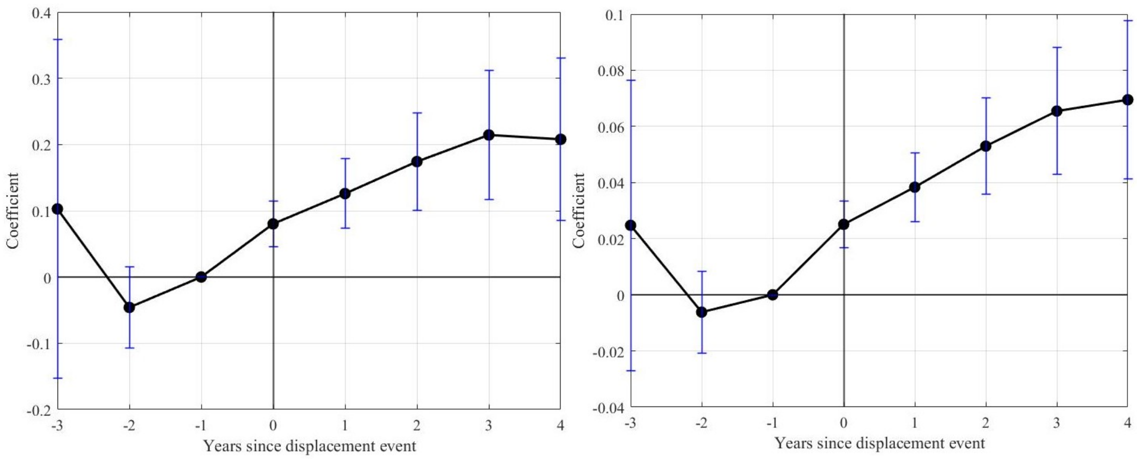
Figure A10: Firms' Productivity and Output, Relative to Year of a Connected Hire Shock - Limited Sample



(a) Productivity (b) Output

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. Sample includes only firms with at least one observation following the event. The bands around the point estimates are 95 percent robust confidence intervals.

Figure A11: Firms' Productivity and Output, Relative to Year of a Connected Worker Displacement - Limited Sample



(a) Productivity (b) Output

Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-3" set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. Sample includes only firms with at least one observation following the event. The bands around the point estimates are 95 percent robust confidence intervals.

Table A24: Output and productivity analysis - Industrial Districts and Industry-specific Human Capital

Dep. var:	**Output**$_t$				**Productivity**$_t$			
Model:	OLS		IV		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connected$_{t-1}$	0.065**	0.027			0.064**	0.032		
	(0.027)	(0.031)			(0.027)	(0.031)		
Hires$_{t-1}$	0.012**	0.014**	0.012**	0.016***	0.013**	0.015**	0.015**	0.018***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Connected$_{t-1}\times$ *Hires*$_{t-1}$	-0.022**	-0.006			-0.020**	-0.007		
	(0.010)	(0.011)			(0.010)	(0.012)		
Connected$_{t-1}\times$ *With.Ind.Distr.*	-0.149		0.707		-0.126		0.759	
	(0.110)		(0.470)		(0.110)		(0.479)	
Connected$_{t-1}\times$ *Hires*$_{t-1}\times$*With.Ind.Distr*	0.077		0.234		0.066		0.684	
	(0.053)		(1.696)		(0.054)		(1.728)	
Connected$_{t-1}\times$ *Same Ind.*		0.073*		0.178*		0.058		0.178*
		(0.041)		(0.103)		(0.041)		(0.105)
Connected$_{t-1}\times$ *Hires*$_{t-1}\times$*Same Ind.*		-0.042**		-0.115		-0.035*		-0.068
		(0.019)		(0.130)		(0.020)		(0.133)
log(K_t)	0.122***	0.124***	0.134***	0.134***				
	(0.020)	(0.020)	(0.020)	(0.020)				
log(L_t)	0.218***	0.217***	0.219***	0.220***				
	(0.023)	(0.023)	(0.023)	(0.023)				
log(M_t)	0.386***	0.389***	0.381***	0.383***				
	(0.014)	(0.014)	(0.014)	(0.014)				
F-stat 1st stage			58.9	241.8			58.9	241.8
R^2	0.98	0.98	0.98	0.98	0.93	0.93	0.93	0.93

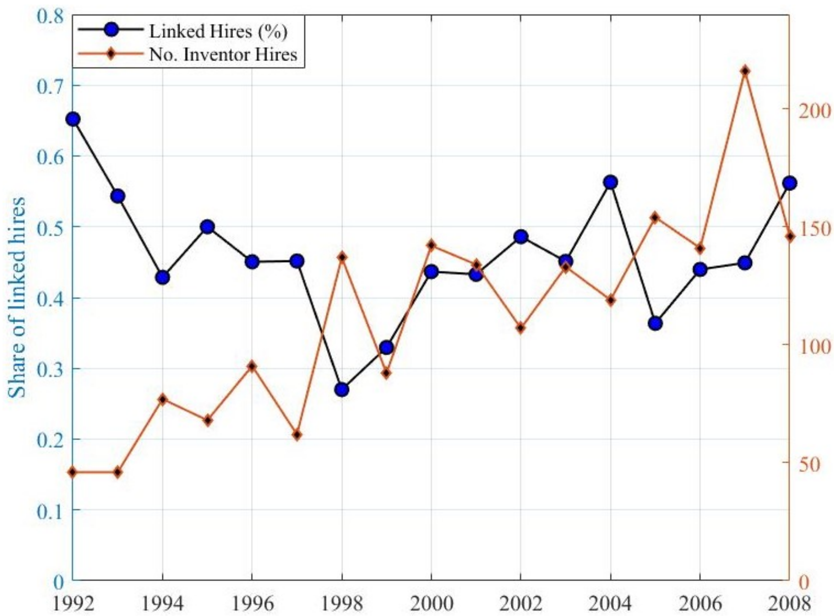
NOTE: Size of the sample for OLS and IV analysis is $4,301$. All models include LLM-year and industry-year fixed effects as well as production inputs (in Output) and firm fixed effects. Variable $Connected$ denotes log number of linked entrants at $t-1$, whereas $Connected \times With.Ind.Distr.$ log number of linked hires within industry clusters in forms operating in those clusters. For identification purposes one cannot include IV for $Connected$ and $Connected \times With.Ind.Distr.$ since they are constructed based on the same variable. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Chapter B

Appendix to Chapter 2

B.1 Additional Results

Figure B1: Share of connected inventor hires (1992-2008)



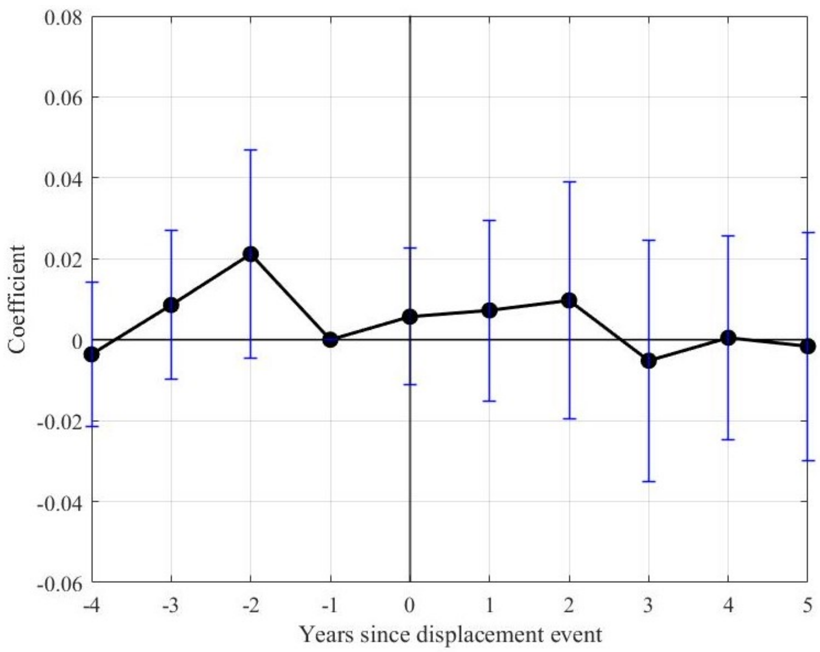
B.1.1 Placebo

Table B1: Impact of Connected Inventor Displacements on Plants' Innovation - Placebo Event Study.

	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
Baseline Sample	0.006	0.009	-0.002	0.004
	(0.009)	(0.011)	(0.013)	(0.010)

Note: Estimates taken from specification of form given in Equation (2.1) where the dependent variable is the number of patents applications. The sample size for *Baseline Sample* is $49, 176$ ($4, 709$ plants), whereas for *Treated only* it is $13, 754$ ($1, 266$ plants). The differences in estimation sample size between baseline event study and the placebo stem from the fact that $i)$ more firms experience multiple placebo effects $ii)$ $Treated$ group is larger in placebo event study. Sample includes only plants with more than 5 observations in the period of interest. The model includes year and plant fixed effects, industry trends and LLM trends, network size, number of displaced workers in the LLM×industry×year. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Figure B2: Plants' Innovation, Relative to the Year of a Connected Inventor Displacement - Placebo



Note: The figure plots point estimates for leading and lagging indicators for the placebo displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

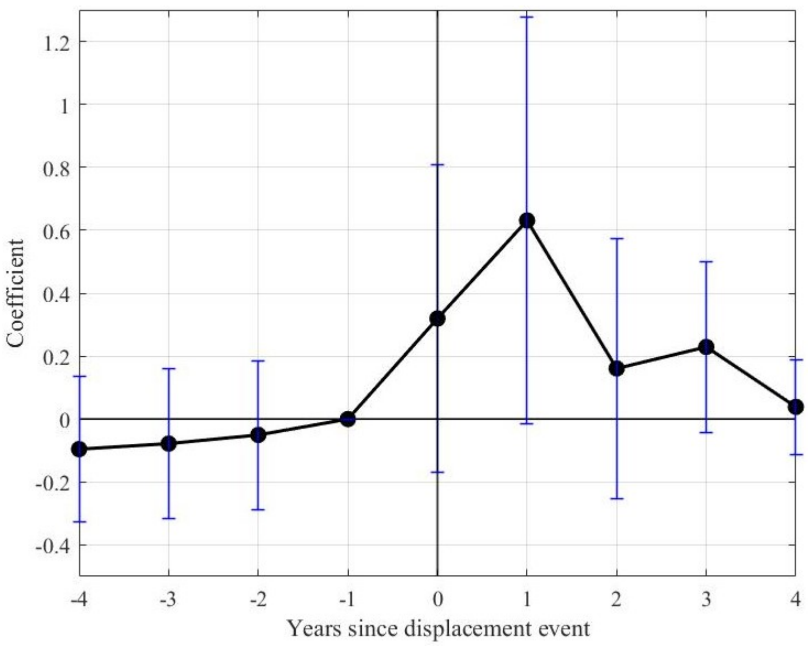
B.1.2 Connected, Displaced Inventor Hire

Table B2: Impact of number of connected, displaced inventor hires on plants' innovative activity - event study.

Dep. Var. *No Patent Applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
Baseline Sample	0.320	0.396*	0.134	0.276*
	(0.248)	(0.232)	(0.095)	(0.166)

NOTE: Note: Estimates taken from specification of form given in Equation (2.1) where the dependent variable is the number of patents applications. The sample size is $81,477$ ($7,385$ plants). Sample includes only plants with more than 5 observations. The model includes year and plant fixed effects, industry trends and LLM trends, network size, number of displaced workers in the LLM$\times$industry$\times$year. Numbers in parentheses are standard errors clustered at the LLM level. $\tau = [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Figure B3: Linked, displaced inventor hires - event study



Note: The figure plots point estimates for leading and lagging indicators for the displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+4" set to 1 for all periods 4 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

B.2 Patent Decomposition

B.2.1 Statistics

Figure B4: Number of patent applications and average number of authors, 1994-2008.

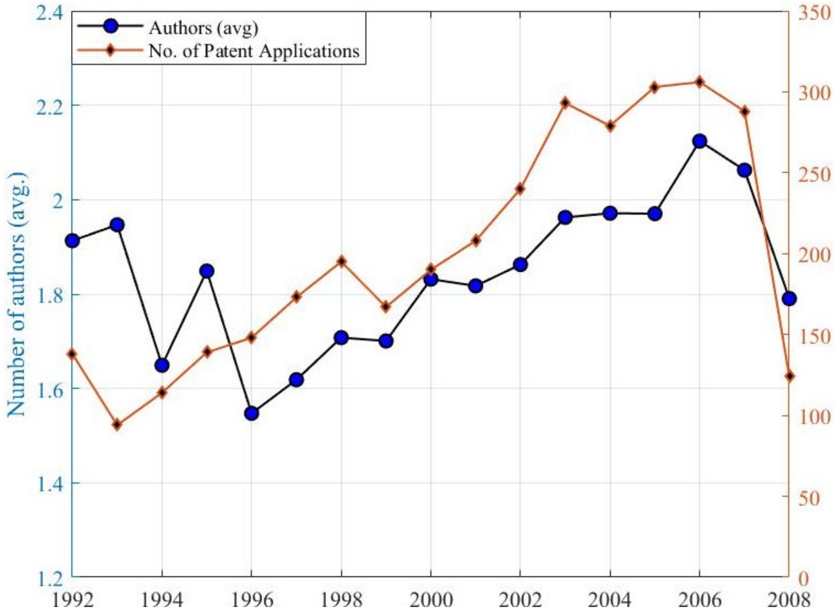
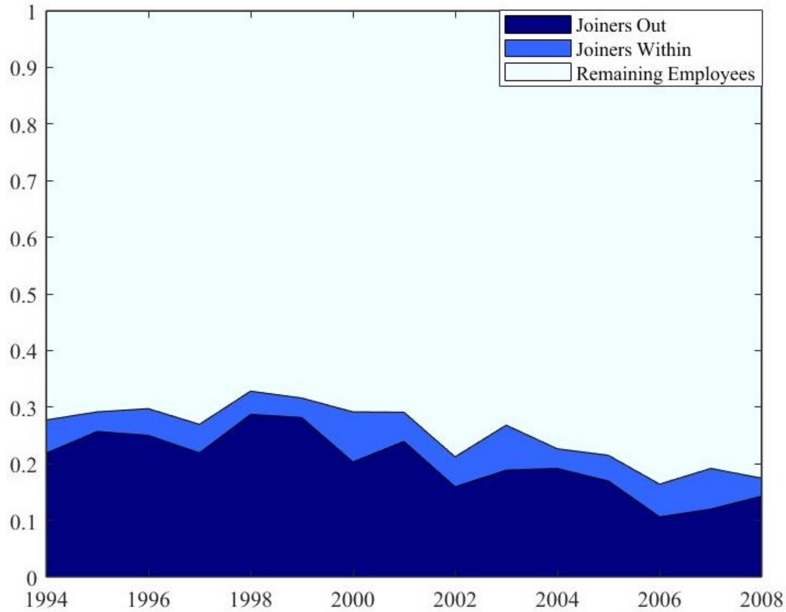
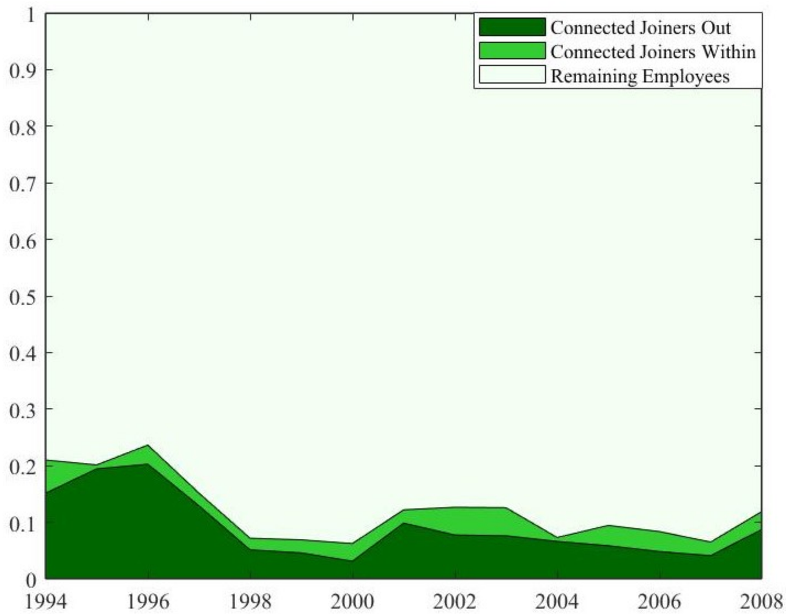


Figure B5: Patent Decomposition - share of patent types, 1994-2008.



(a) Joiners vs. Remaining Employees Applications



(b) Connected Joiners vs. Remaining Employees Applications

Note: Sample of patents is $3,474$. Hires are inventors that entered the plant within past 3 years. 'Old' inventors are remaining co-authors. The hire collaborated patents include applications where hires co-authored with 'old' inventors. In panrl (b) hires are further decomposed into connected and non-connected ones. All of the distinguished categories are mutually exclusive.

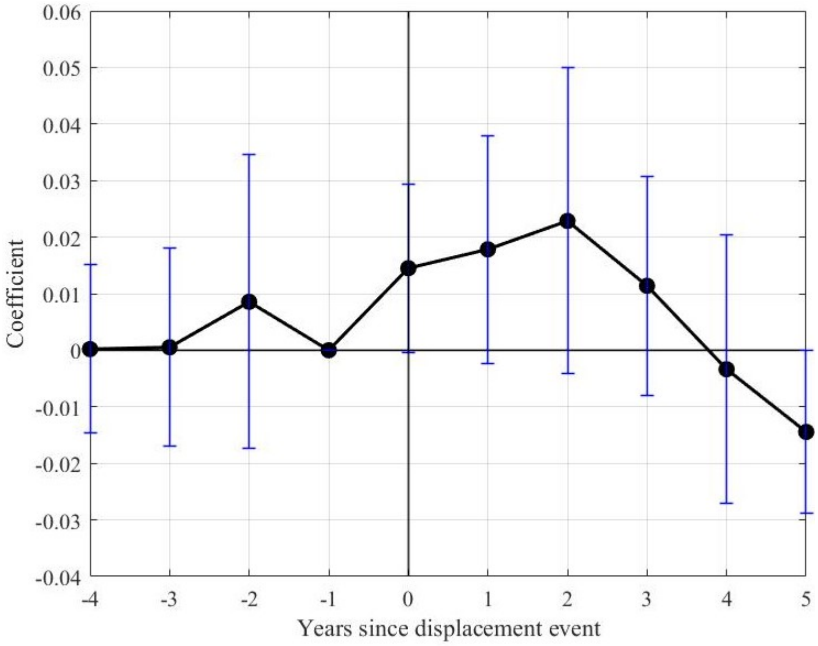
B.2.2 Event Study Decomposition

Table B3: Impact of Connected Inventor Displacements on Plants' Innovation - Event Study Decomposition (5-year window).

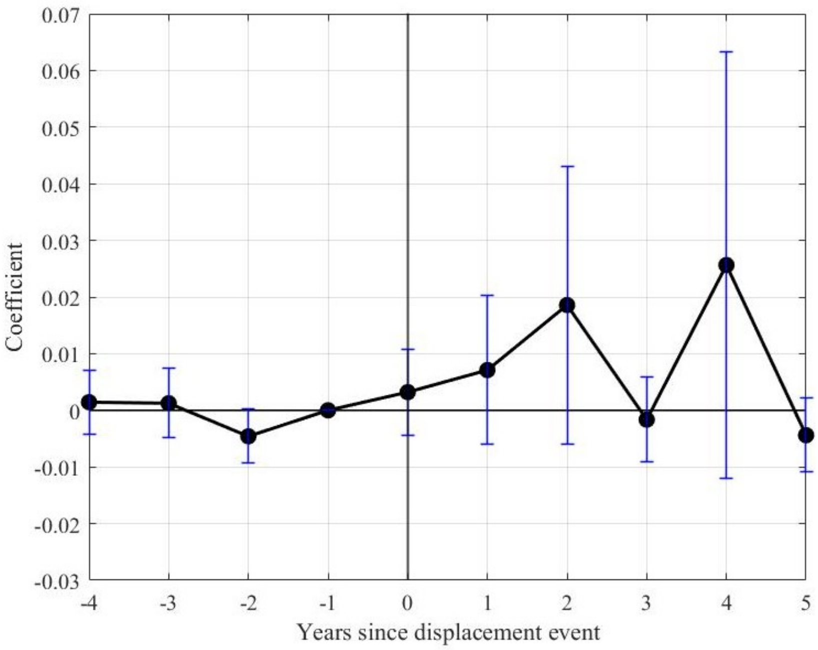
Dependent var.:	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
Connected Joiners Applications				
Single and Outside Co-Author	0.015*	0.020**	0.004	0.013
	(0.008)	(0.010)	(0.009)	(0.008)
Within Plant Co-Author	0.003	0.013**	0.012	0.011*
	(0.004)	(0.006)	(0.009)	(0.006)
Remaining Employees Applications				
Single and Multi-Author	-0.024	0.051*	0.038**	0.031*
	(0.017)	(0.029)	(0.018)	(0.018)

Note: Estimates taken from specification of form given in Equation (2.1) where the dependent variable is the number of patents applications. The sample size is $80,310$ ($7,301$ plants). Sample includes only plants with more than 5 observations in the period of interest. The variable *Connected Joiners Applications (Multi-Author)* is the number of patent applications where at least one of the co-authors is a connected joiner and remaining co-authors are either all from the same plant (*Within*) or mixed (*Outside*). The model includes year and plant fixed effects, industry trends and LLM trends, network size, number of displaced workers in the LLM×industry×year. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Figure B6: Event Study Decomposition - **Connected Joiners** Applications (5-year window)



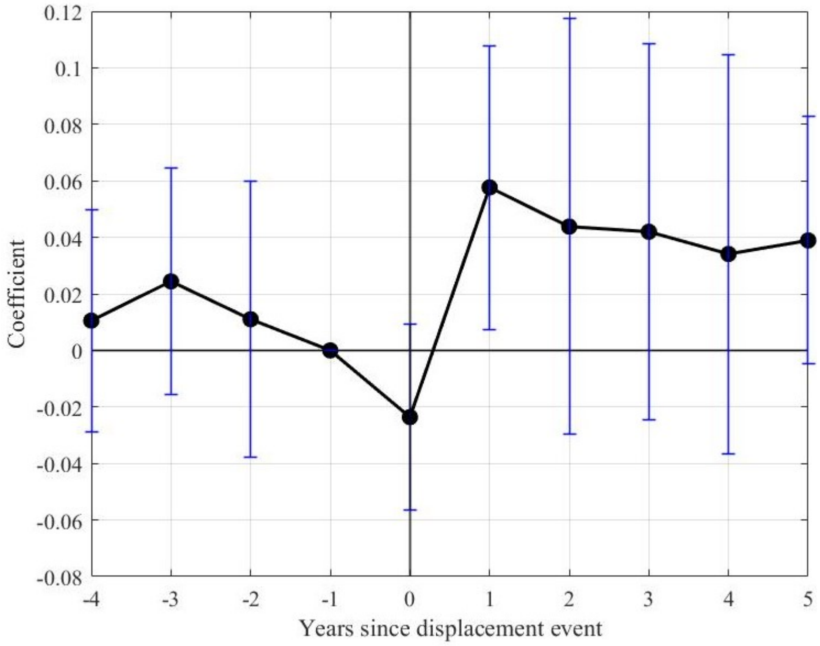
(a) Single and Outside Co-Author



(b) Within Plant Co-Author

Note: The figure plots point estimates for leading and lagging indicators for the placebo displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Figure B7: Event Study Decomposition - **Remaining Inventors** Applications (5-year window)



Note: The figure plots point estimates for leading and lagging indicators for the placebo displacement of a connected inventor. Event time indicator "-4" set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" set to 1 for all periods 5 periods after the event and 0 otherwise. The omitted category is one period prior to the event. The bands around the point estimates are 95 percent cluster-robust confidence intervals (the clustering level is LLM).

Chapter C

Appendix to Chapter 3

C.1 Measure of Job Automation

C.1.1 Baseline measure

Table C1 presents the statistics on the number of industrial robots per thousand of workers in Europe and US using IFR data. European countries comprise nine countries with stock of robots available since 1993: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden and United Kingdom. The number of robots that are not classified in any of the major industry categories accounts for approximately 30% of the stock. Unlike AR, I do not allocate them to industries using their shares from classified robots, hence the minor differences between Table C1 and Table A1 in AR. EU KLEMS does not provide the employment data for Norway, the respective employment counts for Norway were constructed using the industry distribution of employment in remaining Scandinavian countries (Denmark, Sweden and Finland) and the labor force participation in Norway.

C.1.2 Alternative measure

Task measure. As already noted in the paper, the IFR data distinguishes 33 distinct applications of the robots which are later matched to task descriptions provided by O*NET 98. Each occupation is summarized by number of sentences describing detailed tasks required within a job. Key words are then matched with application description. There are more than 12,000 task descriptions, with average of 10 descriptions per occupation. Matching word by word poses several dangers that relate to either opposed meaning (e.g. 'design palletizing (...)' instead of 'palletizing') or repairing tasks, that cannot be performed by industrial robots. To provide better fit also the synonyms of the matched words are checked (e.g. 'position' and 'remove' for application 'packaging, picking and placing'). Having matched applications with task descriptions, I develop two main measures based on:

Table C1: Robot adoption by industry in Europe and United States

	USE OF INDUSTRIAL ROBOTS IN EUROPE										USE OF INDUSTRIAL ROBOTS IN THE UNITED STATES			
	30TH PERCENTILE					MEAN								
	1993	2004	2007	2014	2017	1993	2004	2007	2014	2017	2004	2007	2014	2017
Extractive														
1.Agriculture,forestry and fishing	0.00	0.01	0.03	0.08	0.08	0.00	0.18	0.26	0.39	0.31	0.00	0.00	0.04	0.06
2. Mining and quarrying	0.00	0.00	0.00	0.02	0.16	0.00	1.87	1.87	1.22	1.38	0.00	0.00	0.05	0.06
Manufacturing														
3. Food and Beverages	0.06	1.50	3.07	7.99	8.36	0.37	2.73	4.73	8.58	10.62	0.37	1.59	5.08	6.58
4. Textiles	0.00	0.06	0.11	0.15	0.11	0.23	0.79	0.85	0.92	0.87	0.00	0.00	0.04	0.09
5. Wood and Furniture	0.25	2.57	3.77	4.34	4.15	2.82	7.31	8.36	6.34	5.34	0.00	0.01	0.14	0.29
6. Paper	0.01	0.19	0.23	0.25	0.27	0.21	0.53	0.70	0.74	0.82	0.00	0.00	0.09	0.15
7. Plastic and chemicals	0.87	7.88	12.82	12.44	12.59	2.15	14.16	18.37	15.98	18.05	0.54	2.79	7.91	9.58
8. Glass and ceramics	0.16	0.90	2.35	1.34	1.54	0.72	2.42	3.34	3.90	4.10	0.00	0.09	0.51	1.23
9. Basic metals	0.00	1.64	2.38	4.07	6.40	1.81	3.58	4.65	6.49	7.90	0.00	0.00	5.69	10.68
10. Metal machinery	4.10	7.39	10.69	15.92	19.21	7.28	13.30	17.42	17.46	20.43	0.97	4.42	8.07	7.24
11. Metal products	0.95	0.11	2.59	4.08	4.76	2.25	0.61	2.68	7.34	8.08	0.00	0.00	1.39	1.91
12. Electronics	0.99	1.79	2.47	2.65	1.96	2.33	6.10	6.85	5.03	3.96	0.43	3.20	10.06	15.24
13. Automotive	8.64	18.17	28.74	40.90	43.08	14.34	52.32	60.26	65.51	74.06	10.49	46.88	119.48	146.34
14. Other vehicles	0.05	0.46	0.66	1.51	1.39	2.23	3.88	2.76	2.04	1.97	0.00	0.03	0.36	0.63
15. Other manufacturing	0.59	2.09	1.88	1.46	3.19	3.63	4.28	3.55	3.84	6.07	0.00	0.52	7.74	12.74
Remaining industries														
16. Utilities	0.00	0.01	0.03	0.08	0.13	0.00	0.06	0.10	0.19	0.34	0.00	0.00	0.02	0.10
17. Construction	0.00	0.02	0.05	0.07	0.06	0.00	0.06	0.08	0.11	0.12	0.00	0.00	0.02	0.03
18. Education, research, devel.	0.00	0.11	0.12	0.15	0.17	0.02	0.34	0.38	0.32	0.33	0.00	0.01	0.05	0.11
19. Other non-manufacturing services	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00

Table C2: Robot adoption by occupation in Europe and United States

	USE OF INDUSTRIAL ROBOTS IN EUROPE			
	1993-2000	1993-2007	1993-2012	1993-2016
Highest exposure				
1^{st}	Chemical technicians	Chemical technicians	Punching and stamping M. O.	Punching and stamping M. O.
2^{nd}	Chemical engineers	Chemical engineers	Forging M. O.	Forging M. O.
3^{rd}	Forging M. O.	Separating and filtering M. O.	Chemical technicians	Chemical technicians
4^{th}	Rolling M. O.	Washing, cleaning M. O.	Chemical engineers	Tool and die makers
5^{th}	Metal plating M. O.	Punching and stamping M. O.	Separating, filtering M. O.	Chemical engineers
6^{th}	Washing and cleaning M. O.	Forging M. O.	Tool and die makers	Separating and filtering M. O.
7^{th}	Punching and stamping M. O.	Fabricating M. O., n.e.c.	Washing, cleaning M. O.	Lathe and turning M. O.
8^{th}	Separating and filtering M. O.	Mixing and blending M. O.	Lathe and turning M. O.	Grinding and abrading M. O.
9^{th}	Nailing and tacking M. O.	Tool and die makers	Fabricating M. O., n.e.c.	Fabricating M. O., n.e.c.
10^{th}	Shaping and joining M. O.	Miscellaneous plant and system operators	Grinding and abrading M. O.	Fabricating M. O., n.e.c.
Lowest exposure				
375^{th}	Military occupation	Private HH cleaners and serv.	Insurance adj., examiners	Postal clerks, exc. mail carr.
376^{th}	Managers, farms.	Air traffic controllers	Sheriffs, bailiffs	Public transp.attendants
377^{th}	Managers, horti. spec. farms	Military occupation	Securities and financial ser.	Hotel clerks
378^{th}	Farm workers	Legislators	Private HH cleaners and serv.	Sheriffs, bailiffs
379^{th}	Horticultural spec. farmers	Postmasters and superint.	Mail carriers, postal service	Buyers, wholesale and retail
380^{th}	Judges	Judges	Buyers, wholesale and retail	Priv. HH cleaners
381^{th}	Managers, med. and health	Chief exec. and general adm.	Hotel clerks	Managers, med. and health
382^{th}	Podiatrists	Securities and financial serv.	Bank tellers	Postmasters and superint.
383^{th}	Dental lab and medical tech.	Postal clerks, exc. mail carr.	Managers, med. and health	Legislators
384^{th}	Elevator install. and repairers	Sheriffs, bailiffs	Meter readers	Insurance adj., examiners

Table C3: Robot adoption by occupation group, 1993 - 2016.

		EXPOSURE TO ROBOTS BY OCC GROUPS							
	empl. share	1993-2000	2000-2007	2007-2012	2012-2016	1993-2000	1993-2007	1993-2012	1993-2016
Executive Admin, Managerial	13.87	0.181	0.450	0.163	0.111	0.181	0.631	0.793	0.904
Professional Speciality	13.53	0.112	0.276	0.082	0.050	0.112	0.387	0.469	0.519
Technicians and Related Support	**3.72**	**0.203**	**0.580**	**0.150**	**0.086**	**0.203**	**0.783**	**0.933**	**1.018**
Sales	11.03	0.049	0.124	0.044	0.032	0.049	0.172	0.216	0.248
Admin. Support, incl Clerical	14.70	0.140	0.340	0.124	0.093	0.140	0.480	0.604	0.697
Private Household	0.59	0.005	0.015	0.009	0.007	0.005	0.021	0.029	0.036
Protective Services	1.85	0.049	0.131	0.050	0.037	0.049	0.180	0.229	0.266
Service, except Protective - HH	7.91	0.043	0.102	0.044	0.037	0.043	0.145	0.189	0.226
Farm, Forestry and Fishing	2.94	0.064	0.101	0.044	0.036	0.064	0.165	0.210	0.246
Precision Production, Craft, Repair	**12.33**	**0.353**	**0.940**	**0.421**	**0.313**	**0.353**	**1.293**	**1.714**	**2.027**
Machine Operators, Assemblers, Insp	**7.59**	**0.862**	**2.240**	**0.933**	**0.674**	**0.862**	**3.102**	**4.035**	**4.709**
Transportation and Material Moving	**4.55**	**0.198**	**0.514**	**0.235**	**0.191**	**0.198**	**0.712**	**0.946**	**1.137**
Handlers, Equip, Cleaners, Helpers, Lab	**3.46**	**0.299**	**0.742**	**0.337**	**0.252**	**0.299**	**1.041**	**1.378**	**1.630**

1. Share of applications (tasks/activities) that can be automated
2. Share of tasks that can be automated weighted by the change in robot usage in particular application

The second exposure measure of occupation $o = \{1, 2, ...O\}$ between t and $t+\tau$ is defined as:

$$Exposure_{o,t,t+\tau} = \sum_{a \in \mathcal{A}} \ell_{ao} \Big(\frac{R_{a,t+\tau} - R_{a,t}}{R_{a,t}} \Big) \quad ,$$

where ℓ_{ao} is the share of applications that can be automated within occupation o and the second term is the change or robot usage in application a between t and $t + \tau$ (In this case between 1993 and 2012). Then I distinguish high exposure if the index is above 0 and low exposure otherwise. Threshold of 0 corresponds to 75th percentile of the index. Given that only limited number of occupations in this framework has positive measure, I am not able to distinguish high vs. low exposure in the same fashion as for the baseline measure. Table C5 reports results of both measures and simple dummy equal to one if the index is positive and 0 otherwise. In fact, occupations exposed to automation have higher occupational mobility than those with low risk. The effect is smaller than for baseline measure, the difference stems from the fact that in task based measure I am able to distinguish only high exposure and all remaining occupations, whereas in the baseline measure it is possible to mark high, middle and low exposure occupations.

Second measure. The second alternative measure of the level of automatability for each occupation is based on the work of Frey and Osborne (2017), who classify each

Table C4: Robot adoption by occupation group in Europe and United States

	empl. share	EXPOSURE TO ROBOTS BY OCC GROUPS 1993-2000	2000-2007	2007-2012	2012-2016	1993-2000	1993-2007	1993-2012	1993-2016
		Panel A: **Manual Occupations**							
Professional Speciality	1.10	0.012	0.030	-0.002	0.004	0.012	0.042	0.040	0.044
Technicians and Related Support	**4.40**	**0.119**	**0.351**	**0.061**	**0.041**	**0.119**	**0.470**	**0.531**	**0.572**
Admin. Support, incl Clerical	1.78	0.026	0.061	0.023	0.019	0.026	0.087	0.111	0.129
Private Household	1.74	0.006	0.020	0.011	0.009	0.006	0.027	0.037	0.046
Protective Services	2.75	0.005	0.020	0.009	0.006	0.005	0.025	0.034	0.040
Service, except Protective - Household	1.89	0.004	0.008	0.004	0.003	0.004	0.012	0.016	0.019
Farm, Forestry and Fishing	8.34	0.065	0.101	0.043	0.036	0.065	0.166	0.210	0.245
Precision Production, Craft, Repair	**35.40**	**0.357**	**0.953**	**0.421**	**0.317**	**0.357**	**1.310**	**1.731**	**2.049**
Machine Operators, Assemblers, Insp	**19.68**	**0.797**	**2.073**	**0.867**	**0.638**	**0.797**	**2.870**	**3.736**	**4.374**
Transportation and Material Moving	**13.22**	**0.199**	**0.519**	**0.241**	**0.195**	**0.199**	**0.718**	**0.959**	**1.154**
Handlers, Equip, Cleaners, Helpers, Lab	**9.71**	**0.317**	**0.795**	**0.352**	**0.267**	**0.317**	**1.112**	**1.464**	**1.730**
		Panel B: **Non-manual Occupations**							
Executive Admin, Managerial	**21.74**	**0.190**	**0.475**	**0.172**	**0.118**	**0.190**	**0.665**	**0.837**	**0.955**
Professional Speciality	**20.62**	**0.102**	**0.254**	**0.087**	**0.047**	**0.102**	**0.356**	**0.443**	**0.490**
Technicians and Related Support	**3.47**	**0.093**	**0.256**	**0.097**	**0.051**	**0.093**	**0.349**	**0.446**	**0.497**
Sales	17.29	0.058	0.147	0.051	0.037	0.058	0.204	0.256	0.293
Admin. Support, incl Clerical	**22.07**	**0.126**	**0.314**	**0.114**	**0.082**	**0.126**	**0.440**	**0.553**	**0.636**
Protective Services	1.42	0.047	0.122	0.045	0.033	0.047	0.168	0.214	0.247
Service, except Protective - Household	11.38	0.046	0.115	0.049	0.041	0.046	0.162	0.211	0.252
Farm, Forestry and Fishing	0.13	0.001	0.004	0.002	0.001	0.001	0.005	0.007	0.009
Precision Production, Craft, Repair	0.31	0.002	0.008	0.008	0.003	0.002	0.010	0.018	0.021
Machine Operators, Assemblers, Insp	**1.32**	**0.078**	**0.231**	**0.096**	**0.058**	**0.078**	**0.309**	**0.404**	**0.463**
Transportation and Material Moving	0.04	0.000	0.001	0.000	0.000	0.000	0.001	0.001	0.001
Handlers, Equip, Cleaners, Helpers, Lab	0.21	0.009	0.034	0.020	0.013	0.009	0.043	0.063	0.076

SOC occupation according to how susceptible it is to automation. The following section presents complementary results and robustness check of the aforementioned measure of automatability.

First check. First, let's compare two measures: exposure to automation proposed by Acemoglu and Restrepo (2017a) and the one used in this paper. Figure C1 juxtaposes those two measures on the US territory using Commuting Zones (CZ). First, 722 CZs are distinguished following Autor and Dorn (2013). Panel C1a is taken from Acemoglu and Restrepo (2017a) and measures robot intensity (number of robots per thousand of workers) in each Commuting Zone. Panel C1b presents the share of employment exposed to automation (intensive margin). The grid is for counties, however colors are marked for CZs. Both panels are quite similar, with highest level of automation in the Rust Belt and manufacturing states of the East Heartland (Tennessee, Kentucky, Alabama). The share

Table C5: Occupational mobility and exposure to robots - SIPP 1996-2012

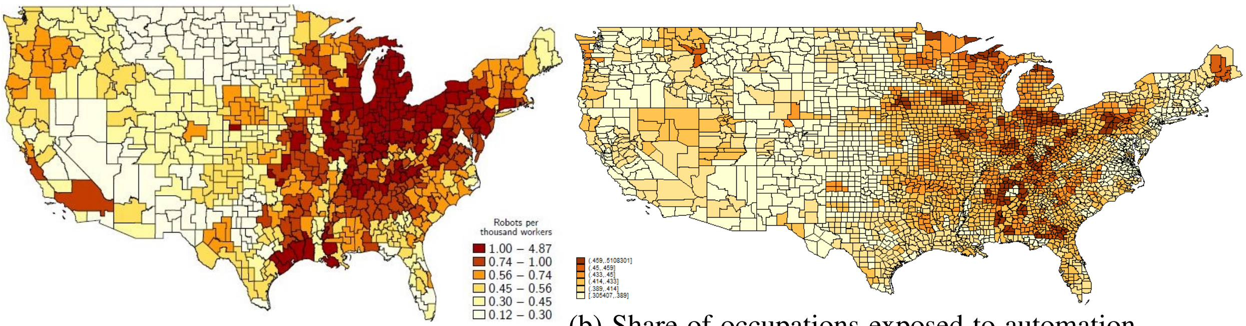
	1 - digit		**2 - digit**		**3 - digit**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: *High exposure - dummy*					
exposure^H	0.039***	0.023**	0.021***	0.028**	0.028***	0.006
	(0.007)	(0.013)	(0.006)	(0.012)	(0.006)	(0.011)
time	-0.004	-0.005	-0.005*	-0.004	-0.002	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
exposure$^H\times$*time*		0.002		-0.001		0.003**
		(0.001)		(0.001)		(0.001)
	Panel B: *Share of automated tasks*					
sh tasks automated	0.097***	0.037**	0.066***	0.034***	0.048***	0.043***
	(0.009)	(0.017)	(0.009)	(0.016)	(0.008)	(0.015)
time	-0.003	-0.005*	-0.004*	-0.005*	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
sh tasks automated$\times$*time*		0.007***		0.000		0.001
		(0.002)		(0.002)		(0.001)
	Panel C: *With change in robots*					
exposure	0.038***	0.031***	0.020***	0.025***	0.014***	0.019***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
time	-0.003	-0.004	-0.004	-0.004	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
exposure$\times$*time*		0.001**		-0.001*		-0.001**
		(0.000)		(0.000)		(0.000)

NOTE: Sample size of the respective panels are $17,731$ (panel A) and $6,556$ (panel B). Control variables include gender, age, its square, duration of non-employment spell, education level (less than high school, high school, some college and graduate degree), state of residence, interaction of time. and age, education level. All observations are weighted by the longitudinal weight. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

of employment is computed from 2010 ACS sample.

Replication. As a next step I replicate the empirical results of Acemoglu and Restrepo (2017a) using my measure of exposure of automation instead the of one proposed by AR. The analysis spans between 1990 and 2007, the regressor of interest is the share of employment exposed to automation in 1990, dependent variables are change in employment to population ratio and log wages (hourly and weekly) between 1990 and 2007. The unit of analysis are Commuting Zones. Table C6 presents the results of long differences model, control variables include demographic characteristics of each Commuting Zone (population, share of female, share of population with college degree, share of Black

Figure C1: Comparison of two measures of exposure to automation, by Commuting Zone



(a) Exogenous exposure to robots 1993-2007, *Acemoglu and Restrepo* (2017)

(b) Share of occupations exposed to automation 2010

and Asians), share of employment in particular industries (manufacturing, durable manufacturing and construction) and exposure to Chinese imports. The covariates are distinguished from 1990 Census and 2007 American Community Survey samples. Results of Table C6 suggest that despite differences in construction, my measure captures the effect observed by AR. The magnitude of the effect is smaller than in AR (compare with Table A3 in AR), however the significant in most of the model specifications.

Worker characteristics. First let's focus on the characteristics of the workers in occupations exposed to automation. The immediate comparison group are routine occupations that were subject to computerization in 90s. It is well documented that those occupations are concentrated in the middle of skill distribution (see Autor et al. (2003)). First let's divide occupations into 3 parts: low, middle and high, depending on the skills required in each type of job. Low skill occupations include health and personal services, cleaning and protection services, machine operators and laborers. Middle skilled occupations comprise production, office and administrative jobs, and sales, whereas highly skilled involve technicians, professionals and managers. The analysed sample doesn't change, includes 29,659 job transitions between 1996 and 2013. Routinness is computed following Autor et al. (2003), occupations above 66^{th} percentile of routinization index are denoted as routine. Routinnes and exposure to automations overlap, especially among middle-skilled workers, however the correlation between indicators of both characteristics is low, around 0.08.

Table C6: Exposure to robots and changes in employment and wages (1990 - 2007 diff.), replication of *Acemoglu and Restrepo* (2017)

	EMPLOYMENT AND WAGE ESTIMATES FOR 1990 - 2007		
	(1)	(2)	(3)
	Panel A: **Private employment to population ratio**		
Automation exposure	-0.33***	-0.17***	-0.09
Routine	-	-	+
	Panel B: **Log wages (hourly)**		
Automation exposure	-0.29**	-0.35***	-0.28*
Routine	-	-	+
	Panel C: **Log wages (weekly)**		
Automation exposure	-0.63***	-0.69***	-0.32*
Routine	-	-	+
N	722	722	722

NOTE: Long-differences estimates of the impact exposure of robots on employment and log wages. Exposure to robots is defined as a share of employment in occupations with high exposure to automation (following Frey and Osborne (2017)). Control variable include demographics (share of female, share of population with college degree, share of Black and Asians), industry shares and exposure to imports from China. All observations are weighted by commuting zone population. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

C.2 Data Construction

Job Transitions and Occupational Mobility. The sample of individuals used in the analysis contains 29,659 job transitions over the years 1996 - 2013. The methodology departs significantly from Carrillo-Tudela and Visschers (2020). The major difference consists in the definition on job transition. Only transitions with non-employment period longer than 3 weeks were taken into account. Hence, all transitions of a type $E-(*)-U-E$ or $E-(*)-N-E$ were permitted. Non-employment period is based on weekly employment status `rkwesr`. The worker is considered as employed if she is 1) With job/business - working, 2) With job/business - not on layoff, absent without pay or 3) With job/business - on layoff, absent without pay. Reemployment date is set from the variable `tsjdate` whereas employer characteristics are obtained from `eeno`, the cross-wave, person specific number of employer. Some works on SIPP data claim that the job beginning date is more reliable than the variable asking if the individual is still working with the same employer as in previous wave (`estlemp`). Only complete non-employment spells are included in the sample, in case of either left or right censoring the spell was discarded. Spells with missing information between displacement and reemployment were also deleted. The SIPP sample design implies than within each panel, first three months have records for less than 4 rotation groups, sample size is smaller. For that reason I only consider months with all 4 rotation gropus in the sample. SIPP data shows the presence the 'seam bias', since individuals are interviewed every 4 months and the effects are stronger between waves. To avoid the 'seam bias', I average the value over 4 months that involve the bias.

I further limit the sample to those employed prior the displacement in private sector, excluding government employees and armed forces. It only includes individuals aged 25-60. SIPP provides information on up to 2 employers, eliminating those with more than 3 jobs prior to non-employment spell does not change the results. Aggregating the data into quarters I first compute monthly occupational mobility and migration rate separately for individuals displaced from jobs with high and low exposure to automation. Monthly values are then aggregated into quarters, missing quarters are not interpolated. As a robustness check I use the methodology proposed by Carrillo-Tudela and Visschers (2020) (hereafter CTV), who construct their sample by looking at monthly employment status. They depart from the methodology described above mainly by approximating monthly employment status by the status declared in the second week of each month and by focusing only on unemployment spells. More precisely, they discard all the non-employment spells where in the month preceding the re-employment, individual declared being out of labor force. For more details on the construction of their final sample look at the Supplementary Appendix A.1 in CTV.

C.3 Automation and Routinization

The following subsection studies the relationship between routinization and automation on the occupational level. The routinization index for 1990 Census occupation classification was taken from David Dorn's webpage.[1]

Figure C2: Share of college educated and routinness by occupational categories, SIPP 1996-2013

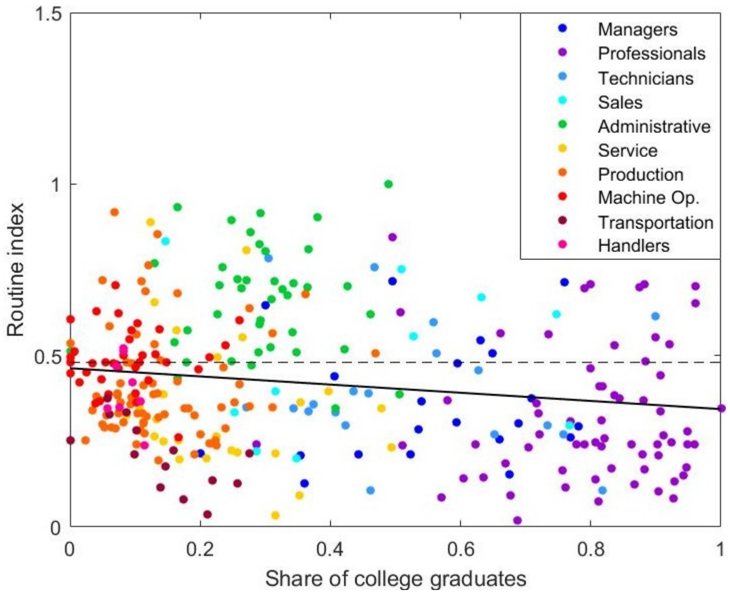
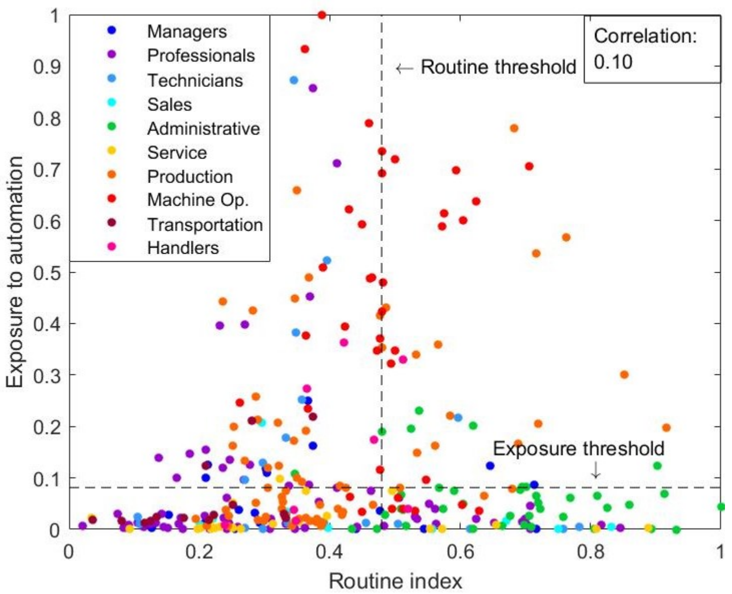


Figure C3: Correlation between routine and automation occupations.



[1]For more on the construction of the measure and available data look at Autor and Dorn (2013) of David Dorn's webpage: https://www.ddorn.net/data.htm.

C.4 Robustness Checks and Additional Material

Table C7: Proportional contribution and direction of occupational mobility, SIPP 1996 - 2013

	Occupational Mobility			
	Contribution	**Direction**		
		All	High exp.	Low exp.
Executive Admin, Managerial	11.09	8.04	4.36	9.06
Professional Speciality	8.6	6.93	6.08	7.7
Technicians and Related Support	2.35	3.11	2.93	2.86
Sales	12.43	14.51	13.76	14.16
Admin. Support, incl Clerical	17.25	16.17	15	21.61
Private Household	0.5	1.91	1.55	2.67
Protective Services	1.24	1.49	1.64	1.17
Service, except Protective - HH	14.82	15.11	14.95	15.59
Farm, Forestry and Fishing	1.53	1.65	2.34	1.05
Precision Production, Craft, Repair	10.7	7.91	9.6	5.41
Machine Operators, Assemblers, Insp	8.04	8.2	10.25	6.28
Transportation and Material Moving	4.27	5.68	6.67	4.29
Handlers, Equip, Cleaners, Helpers, Lab	7.17	9.28	10.88	8.16

Figure C4: Occupational mobility by digit level, only manual occupations. SIPP 1996-2013

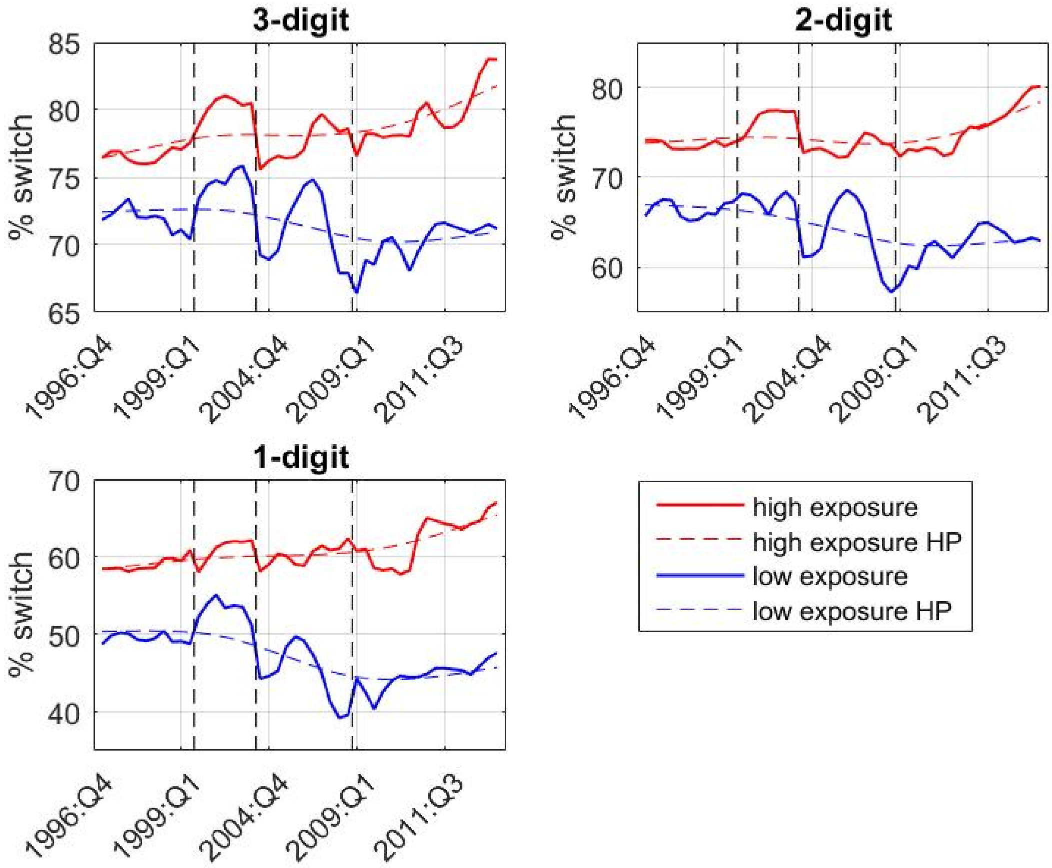


Figure C5: Occupational mobility of routine and non-routine workers - level. SIPP 1996-2013, quarterly.

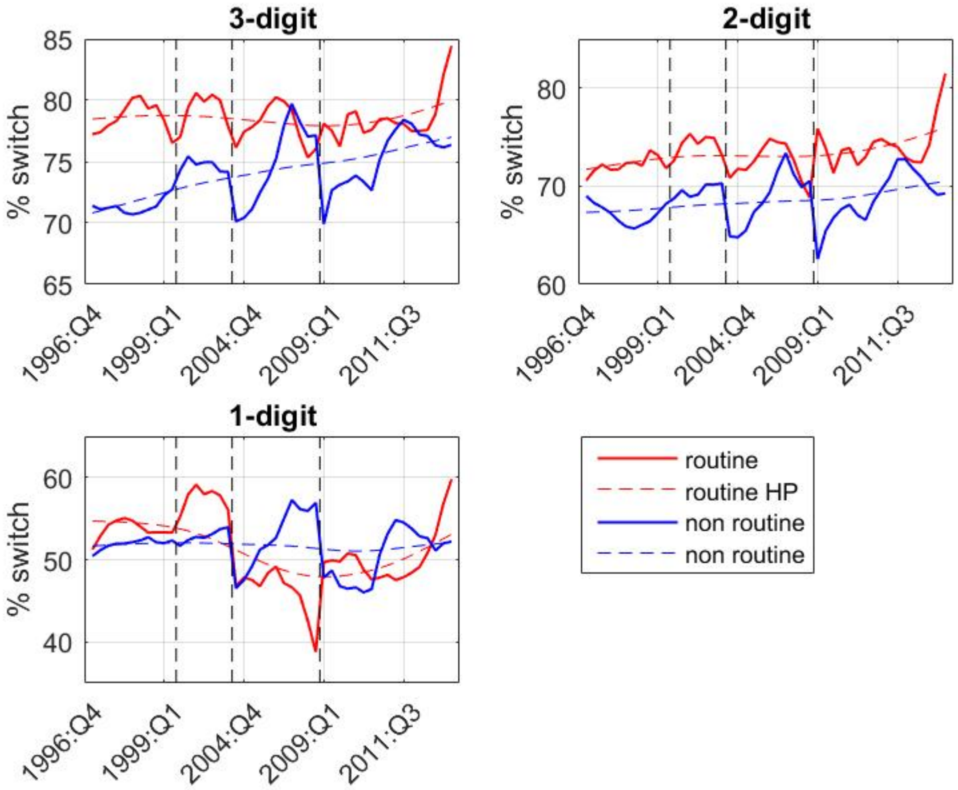


Figure C6: Occupational mobility by digit level. Linked CPS 1976-2017

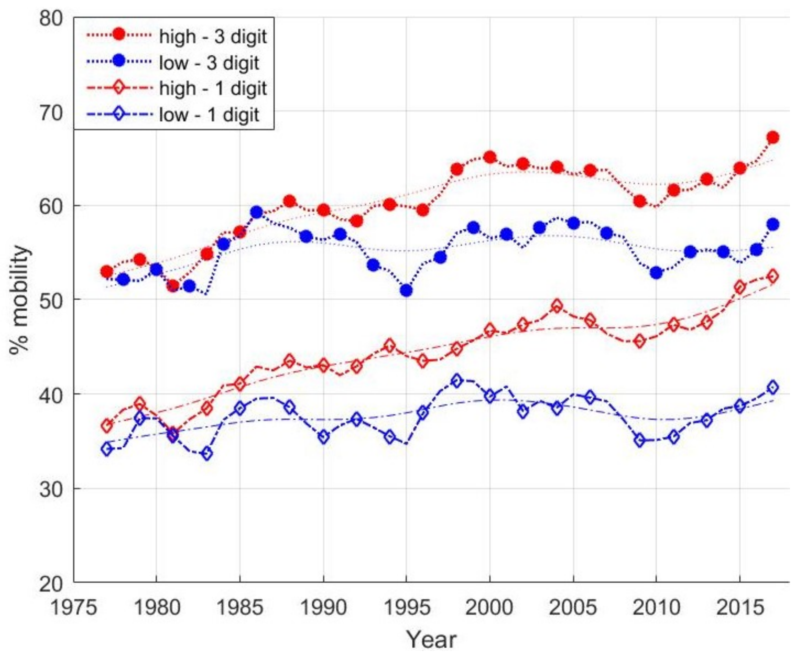


Figure C7: Share of EE transitions among non-employed workers, SIPP 1996-2013.

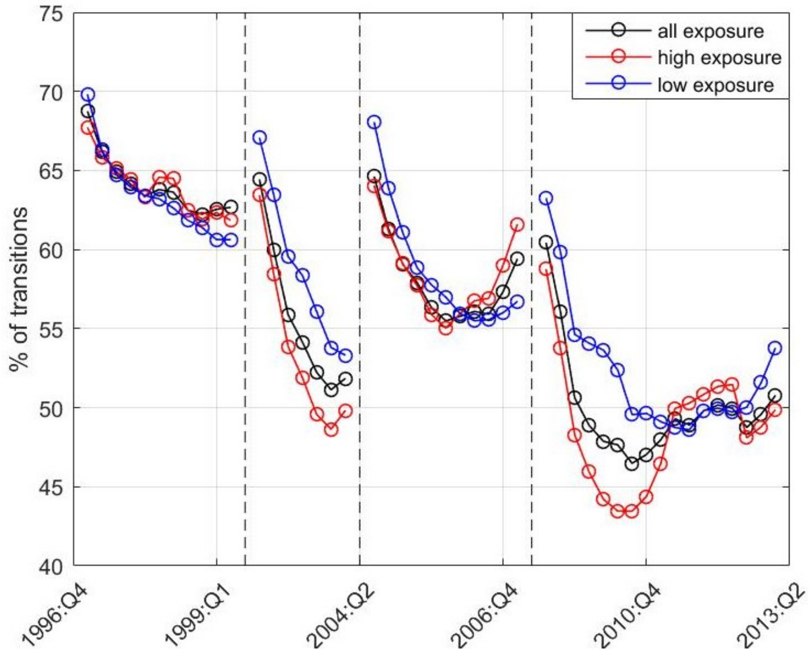


Figure C8: Occupational mobility by digit level- EE transitions. SIPP 1996-2013

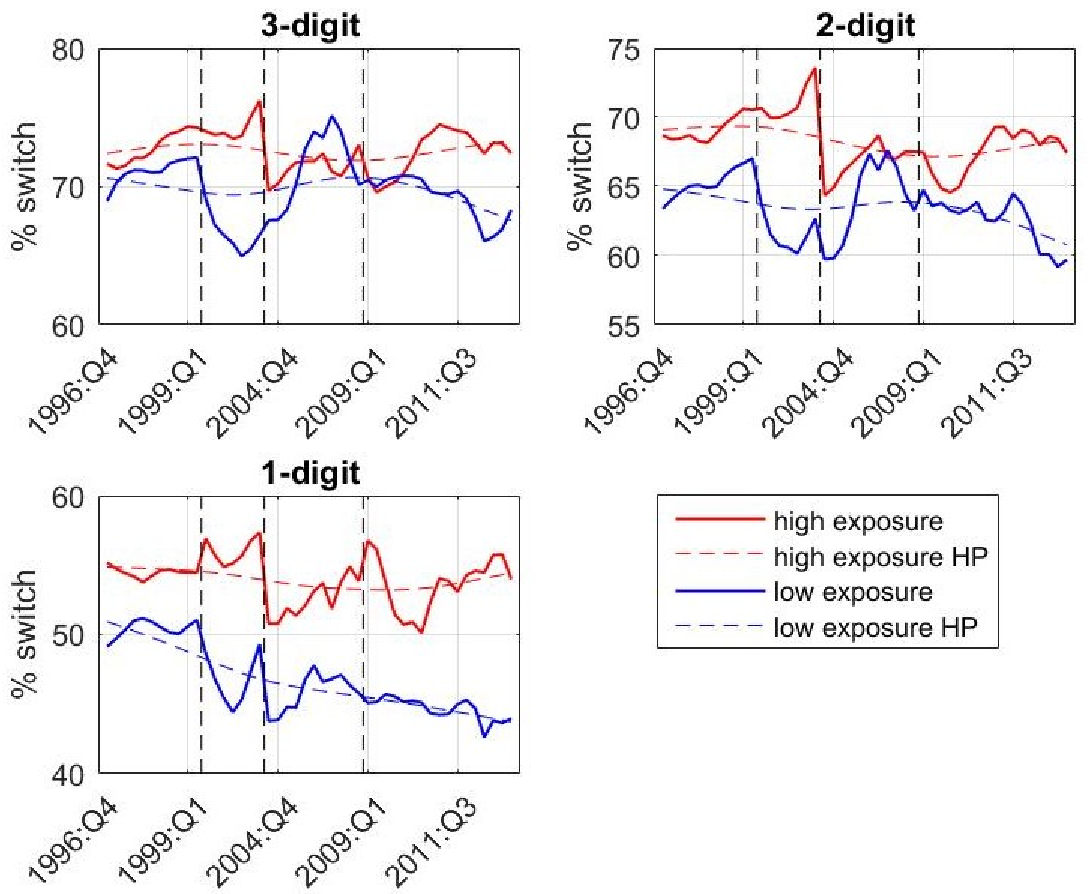


Figure C9: Occupational mobility along wage percentile - EE and E$\not{E}$E transitions. SIPP 1996-2013

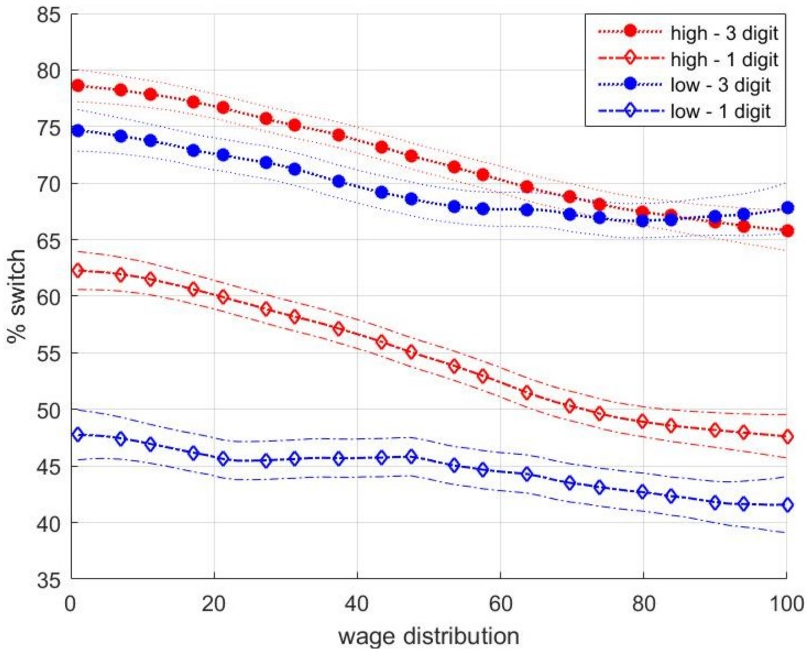


Figure C10: Occupational mobility and life cycle - EE and E$\not{E}$E transitions. SIPP 1996-2013

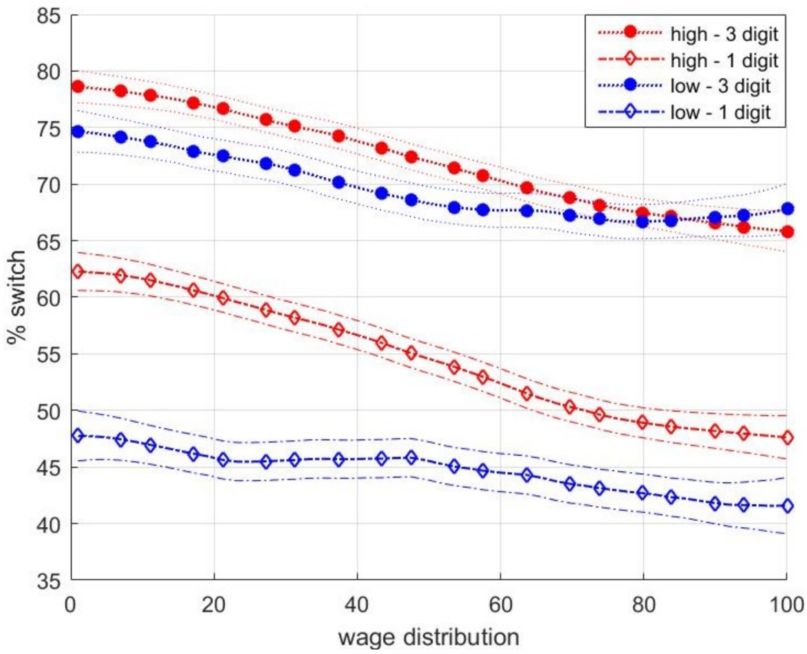


Figure C11: Probability of moving into occupation with higher average wage, conditional on mobility - EE and E$\not{E}$E transitions. SIPP 1996-2013

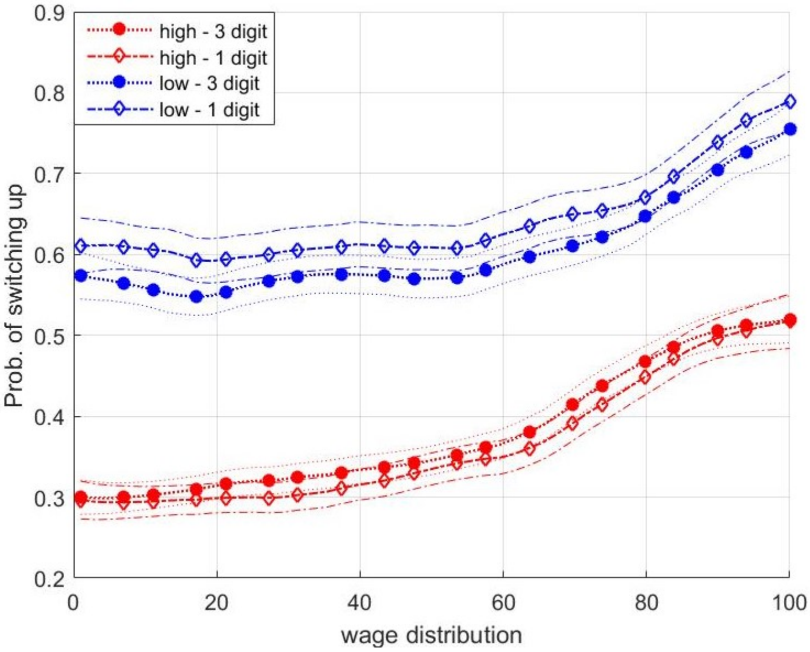
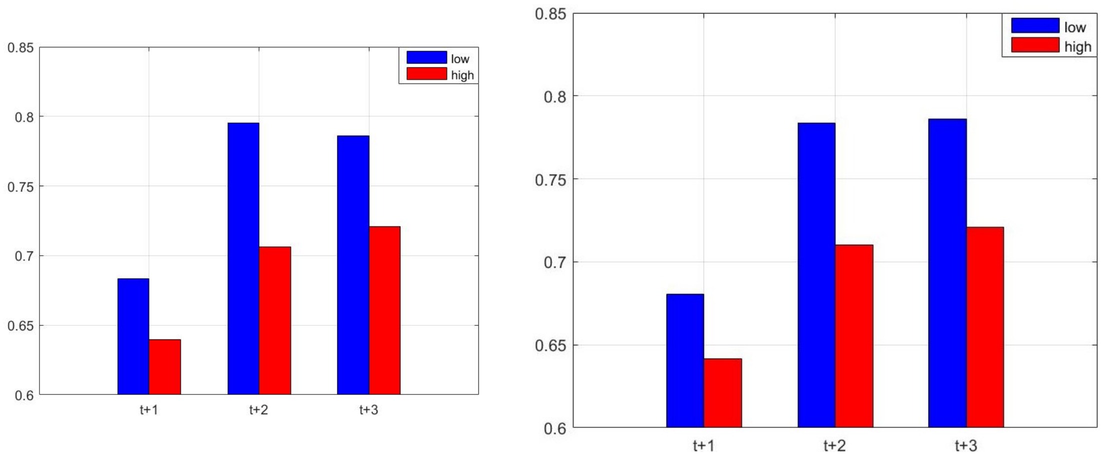


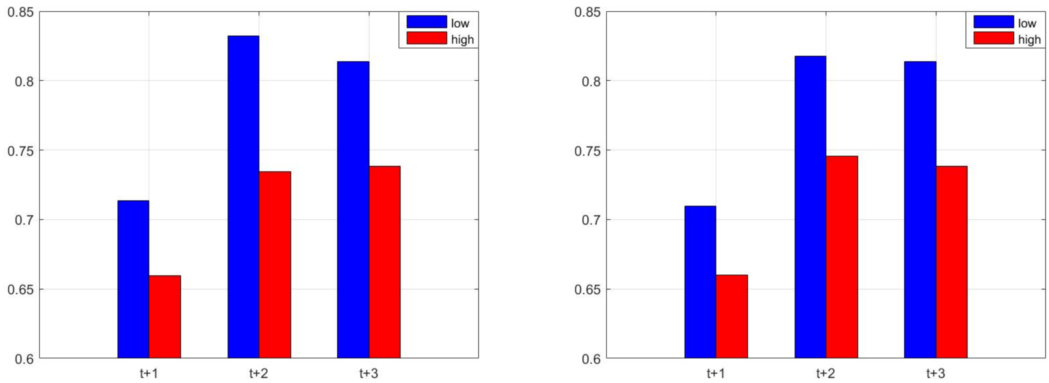
Figure C12: Wage profile of workers who changed occupation as a ratio of stayers' wage, baseline measure. SIPP 1996-2012, average monthly wage



(a) Unbalanced

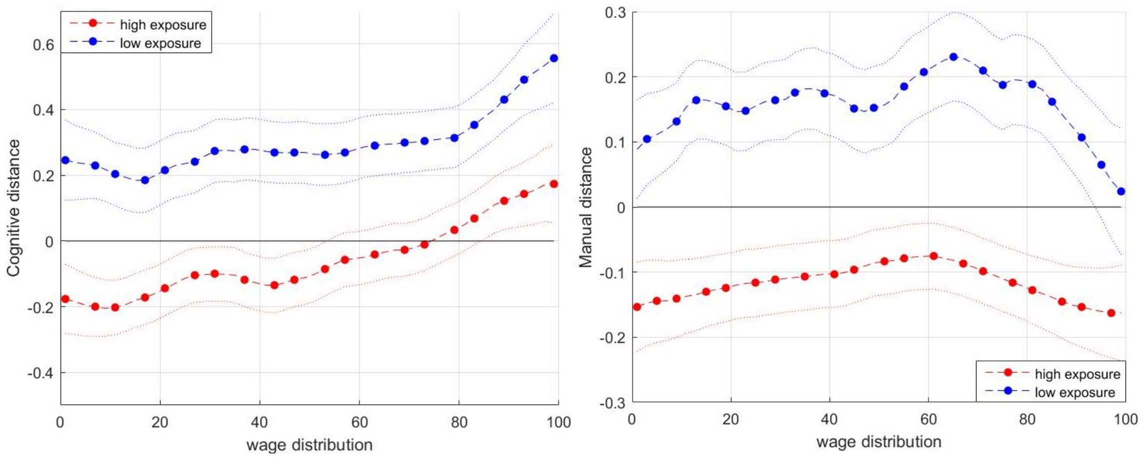
(b) Balanced

Figure C13: Wage profile of workers who changed occupation as a ratio of stayers' wage, baseline measure. SIPP 1996-2012, average weekly wage



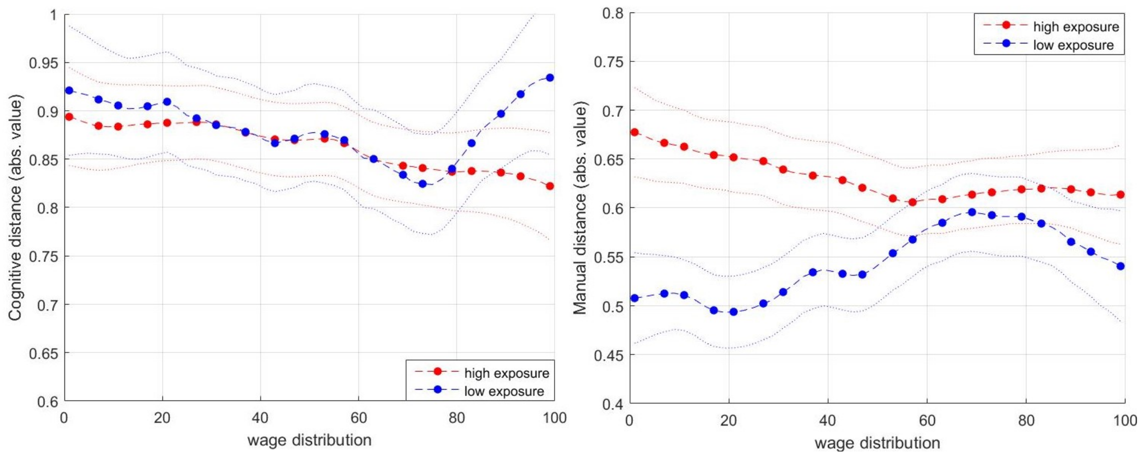
(a) Unbalanced (b) Balanced

Figure C14: Distance of occupational mobility, SIPP 1996-2012.



(a) Cognitive (b) Manual

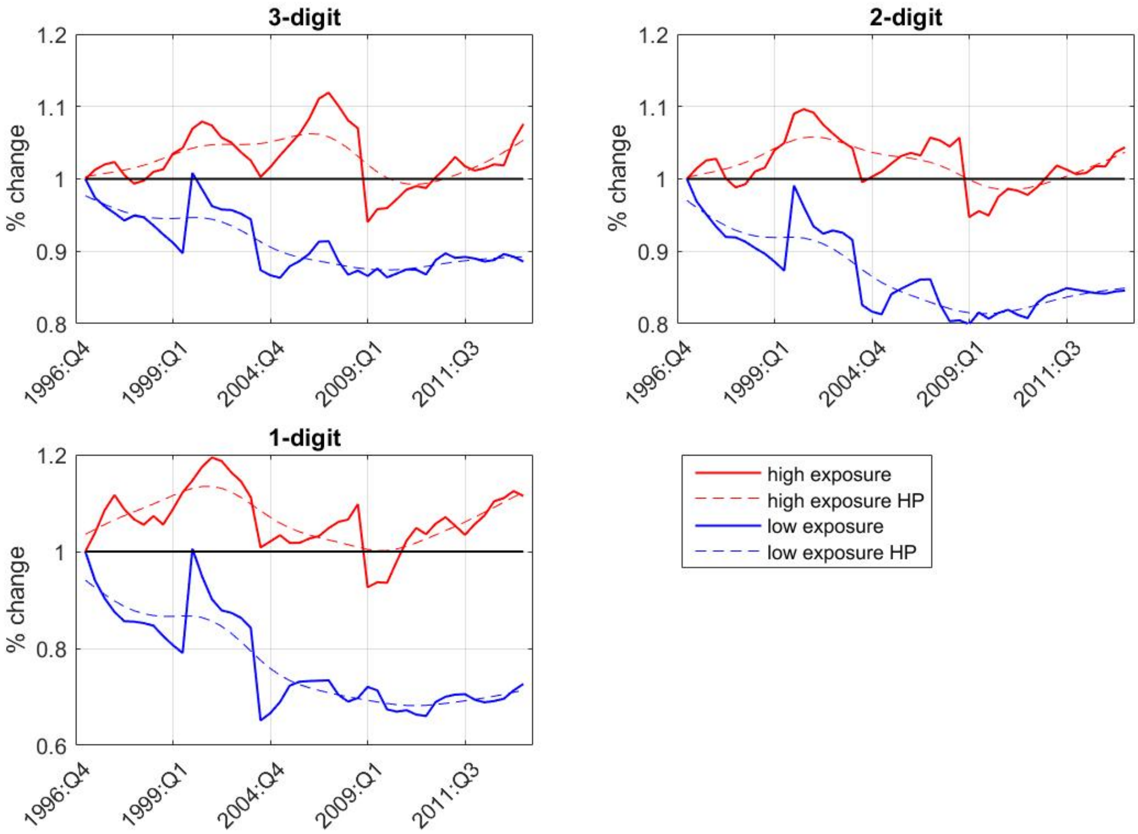
Figure C15: Distance of occupational mobility, absolute value, SIPP 1996-2012.



(a) Cognitive (b) Manual

C.4.1 Results With Alternative Measure

Figure C16: Occupational mobility of workers with high and low exposure to automation (alternative measure). SIPP 1996 - 2013, quarterly.



C.4.2 Occupational Mobility

The first empirical fact is subject to the following econometric model:

$$occ\_mob_{it} = \alpha_1 \cdot exposure_i^H + \alpha_2 \cdot exposure_i^L + \beta \cdot time_t + \gamma \cdot exposure_i^H \times time_t + X\delta + \varepsilon_{it} \tag{C.1}$$

where occ_mob_{it} is discrete variable measuring change of occupation conditional on non-employment spell (1-3 digit level), $exposure_i^k$ equals one if a worker prior to non-employment period had a job with high exposure ($k = H$) or low exposure ($k = L$), $exposure_i^H \times time_t$ is a time trend for workers in occupation exposed to automation. Controls X contain worker characteristics as gender, age, education, non-employment spell state of residence, their time trends, etc. All observations are weighted with the use of longitudinal weights. Subscript t denotes year. Figure **??** presents time coefficients $\gamma(t)$ and $\beta(t)$ for all digit levels with their confidence intervals. Remaining graphs plot results of Model C.1 for various education, gender and unemployment spell groups.

Figure C17: Occupational Mobility - age and education groups, SIPP 3-digit level.

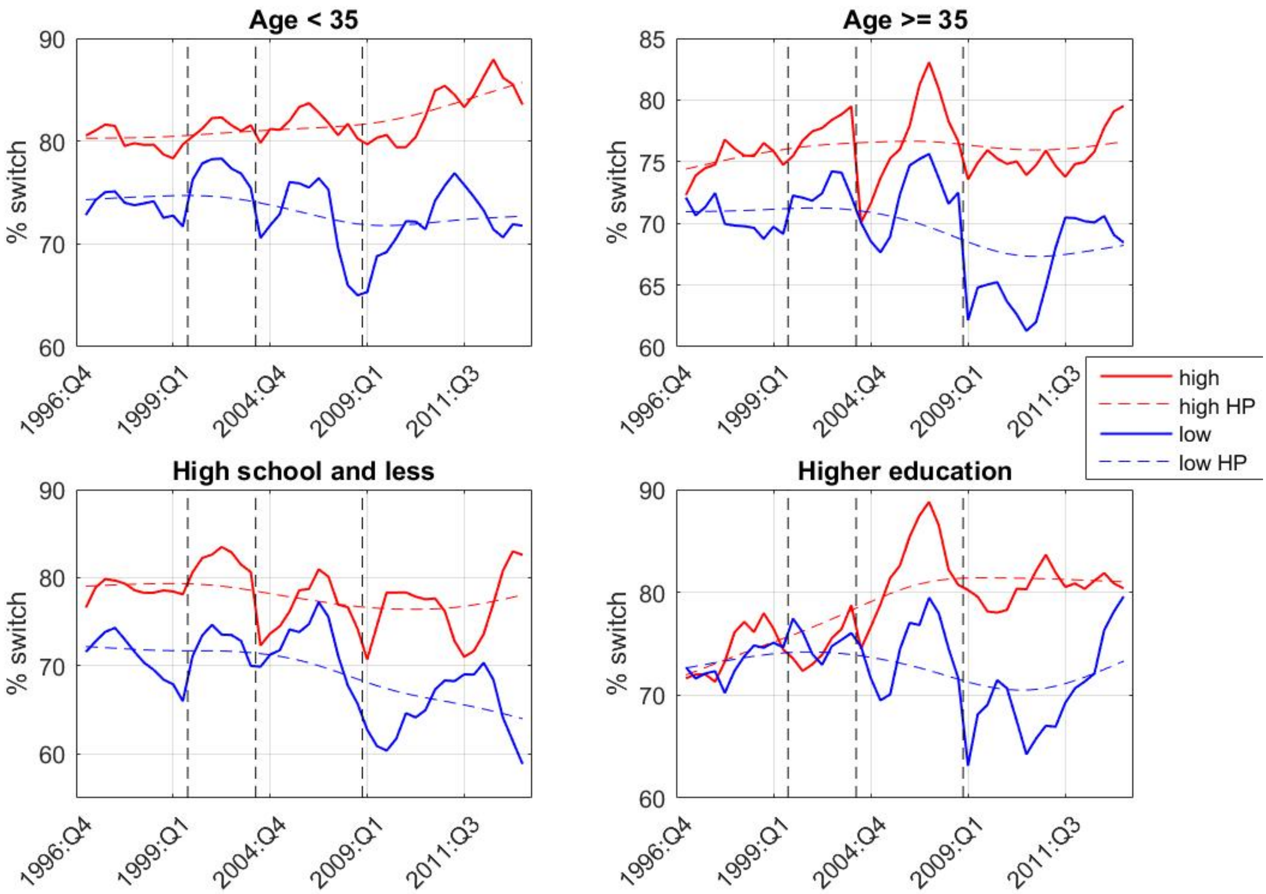


Figure C18: Occupational Mobility - age and education groups, SIPP 1-digit level.

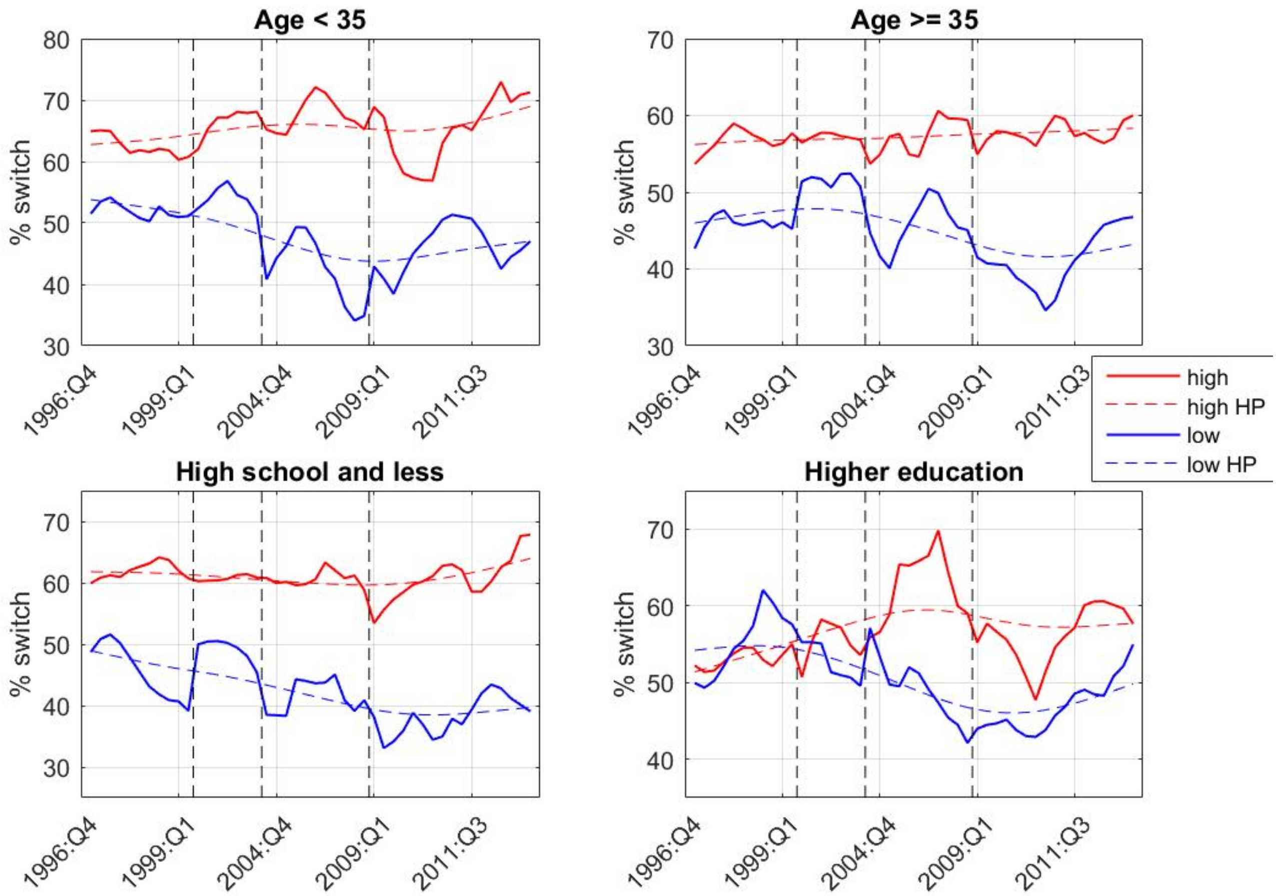


Table C8: Occupational mobility and exposure to robots - SIPP 1996-2012

	1 - digit		**2 - digit**		**3 - digit**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: *Baseline*					
exposure^H	0.145***	0.099***	0.122***	0.093***	0.086***	0.062***
	(0.008)	(0.015)	(0.007)	(0.014)	(0.007)	(0.013)
time	-0.004	-0.006	-0.005*	-0.007**	-0.005	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
exposure$^H \times$*time*		0.005***		0.003**		0.003**
		(0.001)		(0.001)		(0.001)
	Panel B: *Manual occupations*					
exposure^H	0.217***	0.211***	0.157***	0.127***	0.132***	0.086***
	(0.016)	(0.029)	(0.015)	(0.027)	(0.014)	(0.026)
time	0.003	0.002	-0.003	-0.005	-0.002	-0.006
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
exposure$^H \times$*time*		0.001		0.004		0.006**
		(0.003)		(0.003)		(0.003)

NOTE: Sample size of the respective panels are $17,731$ (panel A) and $6,556$ (panel B). Control variables include gender, age, its square, duration of non-employment spell, education level (less than high school, high school, some college and graduate degree), state of residence, interaction of time. and age, education level. All observations are weighted by the longitudinal weight. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Table C9: Occupational mobility and exposure to robots - SIPP 1996-2012

	1 - digit		**2 - digit**		**3 - digit**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: *Age* $<$ *35*					
exposure^H	0.109***	0.109***	0.109***	0.109***	0.101***	0.075***
	(0.022)	(0.022)	(0.020)	(0.020)	(0.010)	(0.019)
time	-0.017	-0.017	-0.008	-0.008	-0.008	-0.009
	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
exposure$^H \times$*time*		0.008***		0.004**		0.003*
		(0.002)		(0.002)		(0.002)
	Panel B: *Age* $\geq$ *35*					
exposure^H	0.117***	0.094***	0.104***	0.084***	0.074***	0.053***
	(0.010)	(0.020)	(0.010)	(0.019)	(0.009)	(0.018)
time	0.007	0.006	0.002	0.001	-0.003	-0.004
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
exposure$^H \times$*time*		0.003		0.002		0.002
		(0.002)		(0.002)		(0.002)
	Panel C: *High school or less*					
exposure^H	0.186***	0.142***	0.144***	0.121***	0.111***	0.087***
	(0.012)	(0.021)	(0.011)	(0.019)	(0.010)	(0.018)
time	-0.011**	-0.011**	-0.007	-0.004	-0.006	-0.004
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
exposure$^H \times$*time*		0.005***		0.003		0.003
		(0.002)		(0.002)		(0.002)
	Panel D: *Higher education*					
exposure^H	0.075***	0.028	0.099***	0.043	0.061***	0.014
	(0.015)	(0.031)	(0.014)	(0.028)	(0.013)	(0.026)
time	0.004	0.002	0.002	-0.001	0.003	0.001
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
exposure$^H \times$*time*		0.005*		0.006**		0.005**
		(0.003)		(0.006)		(0.002)

NOTE: Sample size of the respective panels are $7,267$ (panel A), $10,464$ (panel B), $8,143$ (panel C) and $4,830$ (panel D). Control variables include gender, age, its square, duration of non-employment spell, education level (less than high school, high school, some college and graduate degree), state of residence, interaction of time. and age, education level. All observations are weighted by the longitudinal weight. *$p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

C.4.3 CPS data

Figure C19: Occupational mobility of baseline exposure measure, CPS 1996-2012.

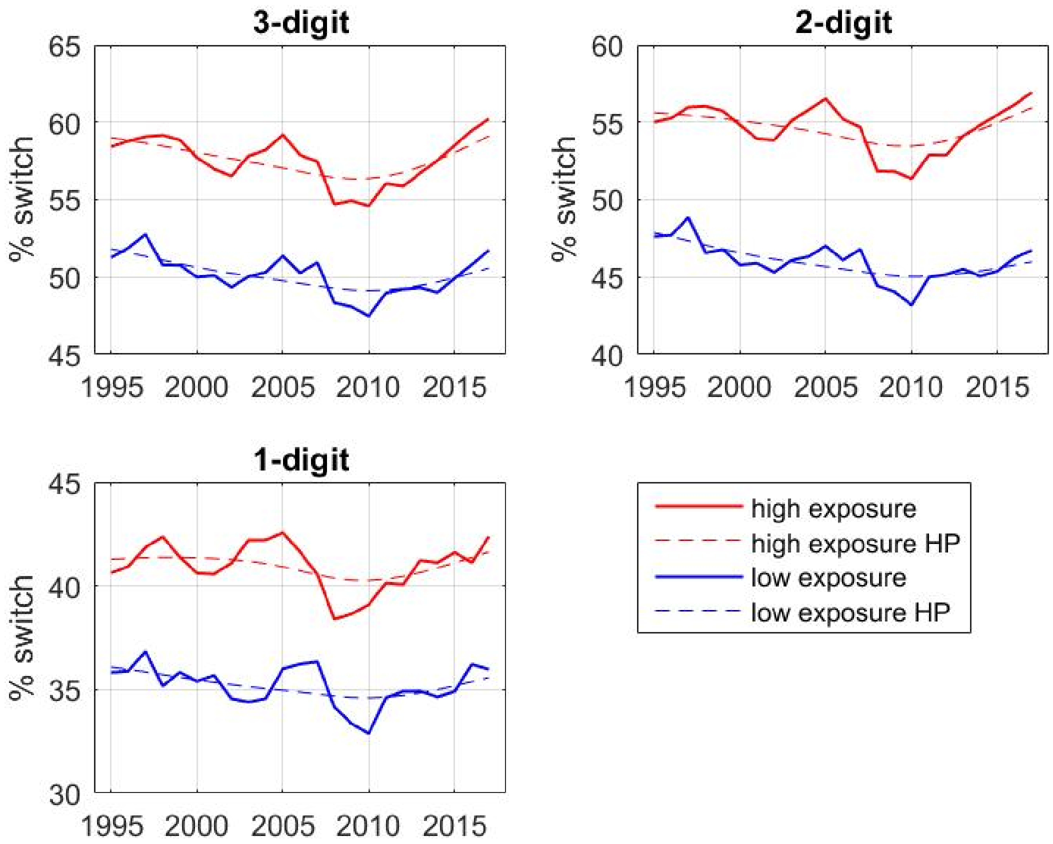


Figure C20: Occupational mobility of manual exposure measure, CPS 1996-2012.

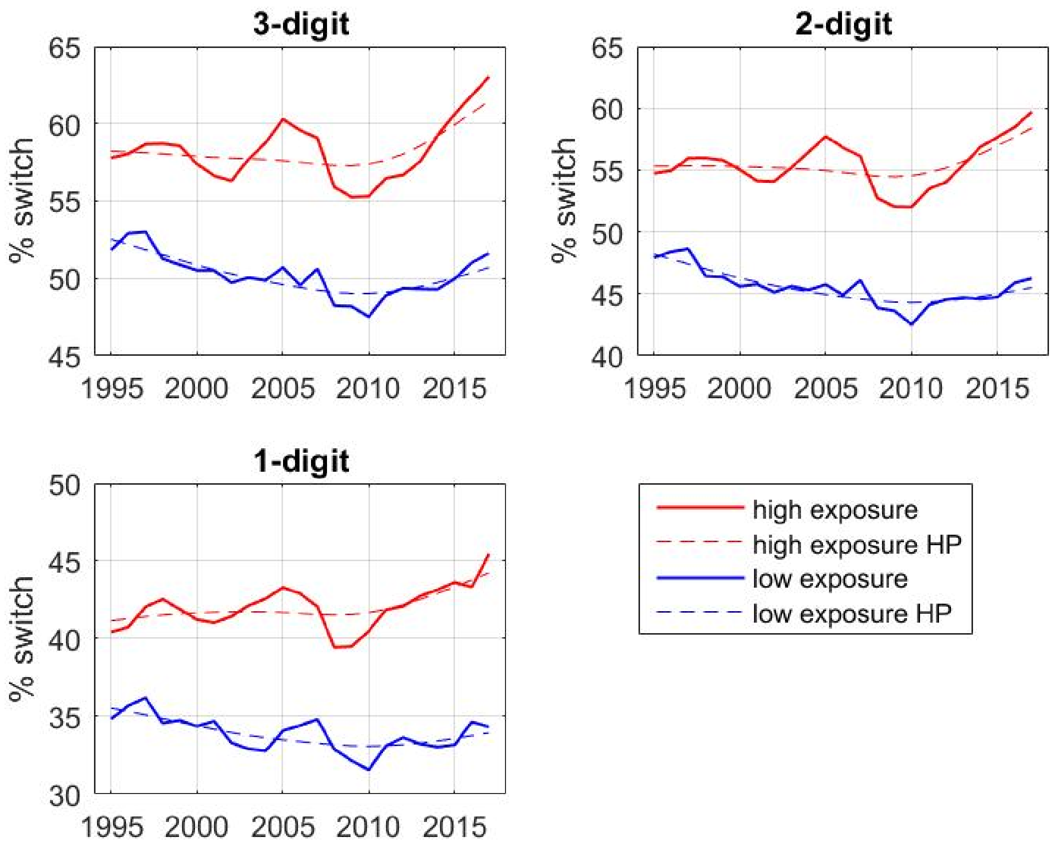
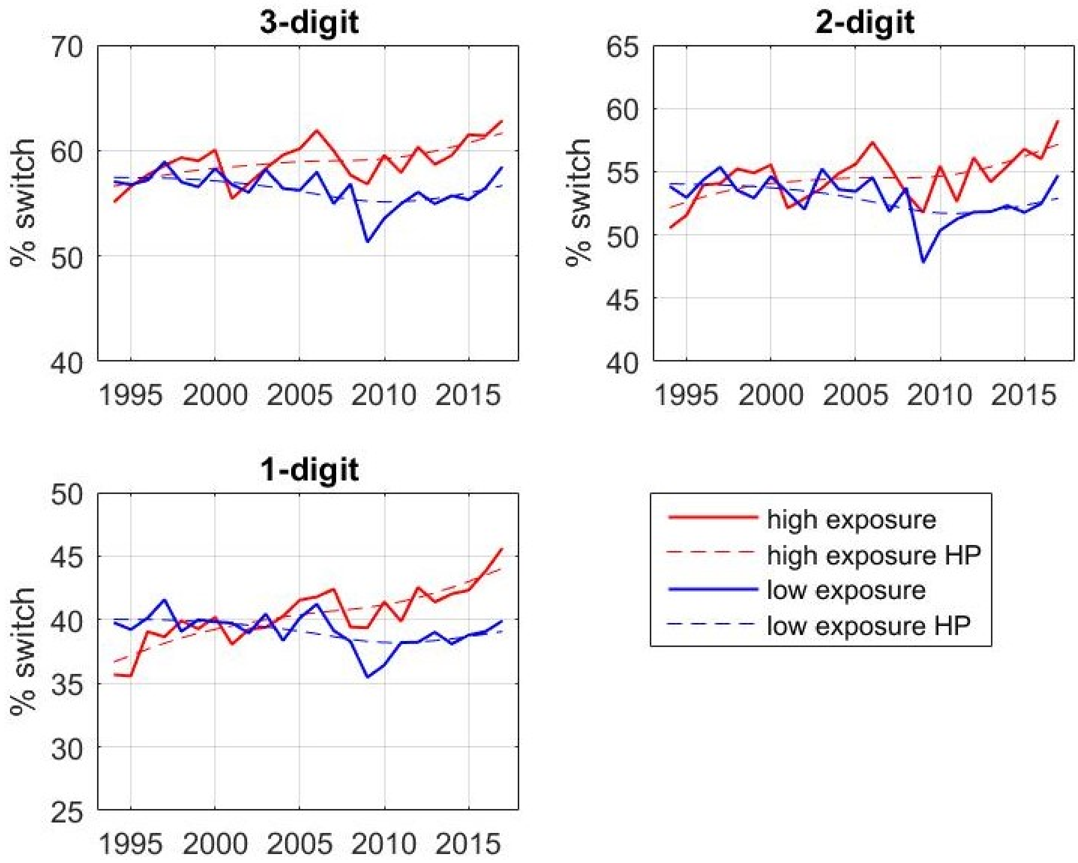


Figure C21: Occupational mobility of workers with high and low exposure to automation (alternative measure). ASEC 1994-2017.



C.5 Model and Calibration Details

C.5.1 Model

Wage Equation. Wages in the models are set through Nash bargaining with α as a bargaining power. They are re-bargained each period given the realization of human capital level. Wage of a match in occupation o with human capital level h_x and tenure $\tau = 1, ..., T$ is given:

$$w^o(\tau, h_x) = \alpha\ q^o(\tau, h_x) + (1-\alpha)\left(1 - \beta\ (1-\xi)\ [\ \mathbf{1}_{(h_x<h_X)}(1-\varphi) + \mathbf{1}_{(h_x=h_X)}\ ]\ \right) - \mathbf{1}_{(h_x<h_X)}\ (1-\alpha)\ \beta\ (1-\xi)\ \varphi\ U^o(h_{x'}) \tag{C.2}$$

where $\mathbf{1}_{(h_x<h_X)}$ is an indicator function equal to one if human capital is lower than the maximum possible level, ξ is the probability of death (retirement).

Worker Flows. The following equations summarize the evolution of number of workers. The number of unemployed workers in the submarket (o, h_x) in the beginning of the period is defined as:

$$
\begin{aligned}
u'(o,h_x) &= \mathbf{1}_{\{x=1\}}\, \xi \Big[\sum_{\tau=1}^{T} e(\tau,o,h_x) + u(o,h_x) \Big] + (1-\xi)\big[(1-\mathbf{1}_{\{x>1\}}\, \varphi^o)\, e(T,o,h_x) \\
&+ \mathbf{1}_{\{x>1\}}\, \varphi^o\, e(T,o,h_{x-1})\big] + (1-\xi) \sum_{\tau=1}^{T} [(1-\delta)\, \psi(\tau,o,h_x) + \delta]\Big((1-\varphi^o) e(\tau,o,h_x) \\
&+ \mathbf{1}_{x>1}\, \varphi^o\, e(\tau,o,h_{x-1})\Big) + (1-\xi)\, (1 - \sum_{o'\neq o} s_{oo'})\, (1-\mathscr{I}^R(o,h_x))\, (1-\lambda^o_{h_x}) \times \\
&\times \Big((1-\mathbf{1}_{\{x>1\}}\zeta)\, u(o,h_x) + \mathbf{1}_{\{x<X\}}\, \zeta\, u(o,h_{x+1})\Big) + (1-\xi) \sum_{o''\neq o} \big(1 - \sum_{o''\neq o} s_{o''o}\big) \times \\
&\times \Big((1-\mathbf{1}_{\{x>1\}}\, \zeta)\, \mathscr{I}^R(o'',h_x)\, (1-\pi_{o''o})\, u(o'',h_x) + \mathbf{1}_{\{x<X\}}\, (1-\zeta)\, \pi_{o''o}\, u(o'',h_{x+1}) \\
&+ \mathbf{1}_{\{x<X-1\}}\, \zeta\, \pi_{o''o}\, u(o'',h_{x+2})\Big) + (1-\xi) \sum_{o''\neq o} \Big((1-\mathbf{1}_{\{x>1\}}\, \zeta)\, s_{o''o}\, (1-\pi_{o''o})\, u(o'',h_x) \\
&+ \mathbf{1}_{\{x<X\}}(\zeta\, s_{o''o}\, (1-\pi_{o''o}) + (1-\zeta)\, s_{o''o}\, \pi_{o''o})\, u(o'',h_{x+1}) + \mathbf{1}_{\{x<X-1\}}\zeta\, s_{o''o}\, \pi_{o''o} \times \\
&\times\ u(o'',h_{x+2})\Big)
\end{aligned}
\tag{C.3}
$$

where $e(\tau, o, h_x)$ is a measure of matches with tenure τ in the submarket (o, h_x), $\psi(\tau, o, h_x)$ equals to one if a match of tenure τ is destroyed due to technological progress and $\mathbf{1}_{\{x=1\}}$ is an indicator function equal to one if $x = 1$. The expression C.3 consists of six major flows. The first one is the share of workers who died (retired) in previous period and were reborn. I assume that the newly born start with the lowest possible level of human capital. The second inflow to unemployment are the workers who in previous period were employed in the maximum tenure T. Matches older than T are destroyed with probability one, workers become unemployed, whereas firms can decide to post a vacancy. The third term in C.3 is the measure of workers employed in period $t-1$ at submarket (o, h_x) who were displaced or individuals from (o, h_{x-1}) who increased their human capital level, however after its realization were subject to either exogenous or technological displacement. The fourth group consists of workers who were unemployed before and neither reallocated of have found a job. The two remaining groups are the workers who reallocated from island o'' to o respectively endogenously or exogenously. The number of newly employed workers in the submarket (o, h_x) (hor whom $\tau = 1$) in the beginning of the period is given by:

$$e'(1, o, h_x) = (1-\xi)\ \big(1-\sum_{o'\neq o} s_{oo'}\big)\ (1-\mathscr{I}^R(o,h_x))\ \lambda^o_{h_x}\Big((1-\mathbf{1}_{\{x>1\}}\ \zeta)\ \times \\ \times\ u(o,h_x) + \mathbf{1}_{\{x<X\}}\ \zeta\ u(o,h_{x+1})\Big) \tag{C.4}$$

where new matches ($\tau = 1$) are formed from unemployed in submarket (o, h_x) who didn't reallocate and those in (o, h_{x+1}) whose human capital depreciated. The measure of employed individuals with matches of tenure $\tau > 1$ is defined as:

$$e'(\tau, o, h_x) = (1-\xi)\ (1-\delta)\Big((1-\mathbf{1}_{\{x>1\}}\ \varphi^o)\ (1-\psi(\tau-1,o,h_x))\ e(\tau-1,o,h_x) \\ +\mathbf{1}_{\{x>1\}}\ \varphi^o\ (1-\psi(\tau-1,o,h_x))\ e(\tau-1,o,h_{x-1})\Big)\quad . \tag{C.5}$$

Matches can either continue in the same human capital level or increase their human capital level with probability φ^o.

C.5.2 Calibration

Step Function. The function $d_{oo'}(h)$ is a key element describing skill transferability between island o and o' given current level of human capital in occupation o: $h \in \{h_1, h_2, h_3\}$. In the first step I construct the matrix that descries the distance between two distinct occupations. The distance is computed from two common indices of task intensity: cognitive and manual. Following the literature they are distinguished from the O*NET database. More precisely, the distance between occupation o and o' is defined as:

$$d_{oo'} = \frac{|cogn.\ idx.^o - cogn.\ idx.^{o'}| + |manu.\ idx.^o - manu.\ idx.^{o'}|}{2}\quad , \tag{C.6}$$

where $cogn.\ idx.$ is index of cognitive tasks intensity, whereas $manu.\ idx.$ is the manual tasks intensity index. The distance is normalized to that it ranges between 0 and 1, where the higher values of $d_{oo'}$ mean higher distance between two occupations. The transition matrix is then:
Upon the mobility from occupation o to o', the new level of human capital in occupation o' can be defined with the step function that uses the distance matrix. The new level of human capital for the displaced workers with h_3 in their old jobs is:

$$\widetilde{h} = h_{x-s} \quad x \in \{2, 3\}, \tag{C.7}$$

where for $x = 3$:

- $s = 0$ if $d_{oo'} \in [0, 0.33)$

Table C10: Distance between occupations

$o\backslash o'$	*1*	*2*	*3*	*4*	*5*	*6*
1	0	0.33	0.39	0.63	0.89	1
2	0.33	0	0.12	0.29	0.56	0.67
3	0.39	0.12	0	0.24	0.50	0.61
4	0.63	0.29	0.24	0	0.26	0.37
5	0.89	0.56	0.50	0.26	0	0.16
6	1	0.67	0.61	0.37	0.16	0

- $s = 1$ if $d_{oo'} \in [0.33, 0.66)$
- $s = 2$ if $d_{oo'} \in [0.66, 1]$

whereas if $x = 2$:

- $s = 0$ if $d_{oo'} \in [0, 0.33)$
- $s = 1$ if $d_{oo'} \in [0.33, 1)$

The reallocation from initial level of human capital h_1 does not incurr any loss of human capital, I assume that the workers start with h_1 in new occupation.

Returns to occupational mobility. Returns to tenure are measured with the use of model in style of *Altonji and Shakotko* (1987), used widely in the labor literature (e.g. Kambourov and Manovskii (2009)). It distinguishes returns to total, tenure, occupational and industrial experience for the panel of employment spells. The econometric model with dependent variable of log real wage takes the form:

$$\begin{aligned} ln(w_{ijmnt}) = \delta_0 Emp\_Ten_{ijt} + \delta_1 Old\_Job_{ijt} + \delta_2 Occ\_Ten_{imt} \\ + \delta_3 Ind\_Ten_{int} + \delta_4 Work\_Exper_{it} + \theta_{it} \end{aligned} \tag{C.8}$$

where Emp_Ten_{ijt}, Occ_Ten_{imt}, Ind_Ten_{int}, $Exper_{it}$ are respectively tenures with the current employer, occupation, industry and labor market. Old_Job_{ijt} is dummy variable equal one from the second year of employment onward. Given (C.8) there is threat of endogeneity, as the residual θ_{it} may be correlated with unobserved individual characteristics that may be decomposed into four components:

$$\theta_{it} = \mu_i + \xi_{ij} + \upsilon_{in} + \epsilon_{it}$$

where μ_i is and individual component, ξ_{ij} a firm component, υ_{in} an industry-match component and ϵ_{it} is an error term. Clearly, the OLS estimation is biased, hence I adopt the instrumental variable approach proposed by *Altonji and Shakotko* (1987). The instrumental variable $\widetilde{X}_{imt} = X_{imt} - \bar{X}_{im}$, where subscript m is the tenure of interest and $\bar{X}$ is the average spell (mean of the spell) in tenure m. Squared and cubed instrumental variables are of the form $\widetilde{X}^2_{imt} = X^2_{imt} - \bar{X}^2_{im}$ and $\widetilde{X}^3_{imt} = X^3_{imt} - \bar{X}^3_{im}$ respectively.

The sample of employment histories is constructed from the 1996 panel of SIPP. It includes individuals aged 25-60 working in the private sector. SIPP panels are quite short and include 3 or 4 year time intervals. The occupational tenure is distinguished using the information in variable `eocctim` that reports length of time in current occupation (in months). It helps with employment spells truncated from the left or individuals who at the time of entry to the sample (first wave) were older than 25 years. Employment tenure in the spells truncated from the left is cumputed with the use of `tsjdate` - a variable that denotes starting year and month of the current job. Unfortunately, in the SIPP data it is impossible to distinguish industry tenure, keep in mind however, that in Kambourov and Manovskii (2009) returns to industry tenure didn't bring much information. As a control variables I use age, its square, gender,industry-, occupation- and time-fixed effects. The final sample contains 94,939 observations for 32,022 distinct employment spells.

Table C11: Returns to occupational tenure - results

dep. variable:		Occupational groups					
$ln(w_{ijmnt})$	All	(1)	(2)	(3)	(4)	(5)	(6)
Employer tenure	0.0079***	0.0036	0.0180***	-0.0028	0.0117***	0.0037	-0.0030
	(0.0013)	(0.0024)	(0.0029)	(0.0048)	(0.0044)	(0.0027)	(0.0051)
Emp. ten.^{2} $\times$ 100	-0.0203***	0.0061	-0.0409***	0.0028	0.0340***	-0.0308***	0.0219*
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Occupation tenure	0.0282***	0.0316***	0.0184***	0.0438***	0.0318***	0.0245***	0.0223***
	(0.0018)	(0.0037)	(0.0038)	(0.0060)	(0.0056)	(0.0035)	(0.0059)
Occ. ten.^{2} $\times$ 100	-0.0494***	-0.0494**	-0.0504	-0.1235***	-0.1235***	-0.0439**	0.0347
	(0.0001)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0004)
Occ. ten.^{3} $\times$ 100	0.0002	-0.0001	-0.0002	0.0012*	0.0016**	0.0001	0.0001
	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Old Job	0.6247***	0.0910	0.3308	1.3588***	1.5328***	1.2165***	1.8007***
	(0.0986)	(0.1760)	(0.2210)	(0.3687)	(0.3078)	(0.2088)	(0.3865)
Total Experience	-0.0178***	-0.0243***	0.0005	-0.0055	-0.0118	-0.0033	0.0183
	(0.0026)	(0.0046)	(0.0064)	(0.0099)	(0.0082)	(0.0063)	(0.0227)
Experience^2 $\times$ 100	-8.7760***	-9.7544***	-12.5005***	-15.8646***	2.0341	-8.1881***	-8.6336***
	(0.0026)	(0.0106)	(0.0134)	(0.0207)	(0.0164)	(0.0126)	(0.0227)
Experience^3 $\times$ 100	4.6500***	4.2623***	5.5405***	8.4068***	0.7031	3.1407***	3.7713***
	(0.0035)	(0.0073)	(0.0087)	(0.0125)	(0.0095)	(0.0075)	(0.0131)
N	94,252	30,844	18,167	8,846	10,315	17,416	7,186
Individuals	25,476	8,501	5,412	2,749	3,089	4,979	2,245

Additional Parameters

Table C12: Remaining parameters - $s_{oo'}$

$o \backslash o'$	*1*	*2*	*3*	*4*	*5*	*6*
1	0	0.2160	0.1325	0.0364	0.0450	0.0444
2	0.1410	0	0.1294	0.0010	0.0664	0.0534
3	0.1095	0.1793	0	0.1269	0.0827	0.0673
4	0.0512	0.0952	0.1209	0	0.1113	0.0872
5	0.0233	0.0826	0.0649	0.0000	0	0.1696
6	0.0383	0.0686	0.0667	0.0467	0.2342	0

NOTE: the diagonal values are not a parameters.

Additional Moments

Table C13: Occupational mobility across islands - DATA/MODEL

$o \backslash o'$	*1*	*2*	*3*	*4*	*5*	*6*
1	0.471/0.470	0.216/0.216	0.132/0.132	0.092/0.093	0.045/0.045	0.044/0.044
2	0.140/0.141	0.515/0.512	0.129/0.129	0.097/0.098	0.066/0.066	0.053/0.053
3	0.110/0.110	0.179/0.179	0.435/0.433	0.127/0.127	0.082/0.083	0.067/0.067
4	0.051/0.051	0.096/0.095	0.121/0.121	0.534/0.534	0.111/0.111	0.087/0.087
5	0.038/0.038	0.082/0.083	0.065/0.065	0.109/0.108	0.537/0.537	0.169/0.170
6	0.038/0.038	0.069/0.069	0.077/0.076	0.119/0.119	0.234/0.234	0.464/0.463

Table C14: Calibration - additional moments

non-targeted moment	Data	SS	non-targeted moment	Data	SS
$\hat{UE}^{H}$	0.762	0.506	$\hat{EU}^{H}$	0.064	0.089
$\hat{UE}^{M}$	0.822	0.664	$\hat{EU}^{M}$	0.048	0.061
$\hat{UE}^{L}$	0.779	0.934	$\hat{EU}^{L}$	0.073	0.051
$\hat{UE}^{h_1}$	0.773	0.810	$\hat{EU}^{h_1}$	0.079	0.055
$\hat{UE}^{h_2}$	0.784	0.733	$\hat{EU}^{h_2}$	0.037	0.079
$\hat{UE}^{h_3}$	0.795	0.937	$\hat{EU}^{h_3}$	0.029	0.063
$\frac{wage^{o\in H}}{wage^{o\in L}}$	0.949	0.887	$occ.mob.^{o\in H}$	0.513	0.521
$\frac{wage^{o\in H}}{wage^{o\in M}}$	0.696	0.969	$occ.mob.^{o\in M}$	0.506	0.509
$\frac{wage^{o\in L}}{wage^{o\in M}}$	0.733	1.093	$occ.mob.^{o\in L}$	0.499	0.501
$unempl$	0.046	0.071	$\%of\ endog.\ sep.$	-	34%

C.5.3 Policy Proposals

Off-the-Job Training. To perform policy counterfactual I first construct new distance matrix that relates human capital loss to difference in training and educational requirements between two occupations. I use the information on training and education requirements for each occupation from O*NET and SIPP. The latter dataset contains only the information on the education requirements (average educational attainment of individuals employed in particular occupation). To check the importance of training and educational differences on wage loss during occupational mobility I construct the following model:

$$wage_{o'}^{E\not{E}\mathbf{E}}/wage_{o}^{\mathbf{E}\not{E}E} = \beta_0 + \beta_1|Dist.Edu._{oo'}| + \beta_2|Dist.Exper._{oo'}| + \beta_3|Dist.Otj.Tr._{oo'}| + \beta_4|Dist.Plant\,Tr._{oo'}| + \varepsilon_{oo'} \tag{C.9}$$

where $wage_{o'}^{E\not{E}\mathbf{E}}/wage_{o}^{\mathbf{E}\not{E}E}$ is average wage loss from moving from occupation o to o' and the regressors are the absolute distance in education, experience, on-the-job and plant training respectively. Table C15 presents the results from measures derived from O*NET and SIPP datasets. The findings suggest that only the difference in educational

Table C15: Impact of training and educational differences on wage loss during occupational mobility, O*NET and SIPP.

Dependent variable	**O*NET**		**SIPP**	
$wage_{o'}^{E\not{E}\boldsymbol{E}}/wage_{o}^{\boldsymbol{E}\not{E}E}$	(1)	(2)	(3)	(4)
Distance				
Education	-0.234**	0.145	-0.026**	-0.030***
	(0.121)	(0.106)	(0.011)	(0.011)
Experience	-0.156	0.227**		
	(0.110)	(0.106)		
On-the-job training	0.093	0.354		
	(0.222)	(0.251)		
Plant training	-0.038	0.002		
	(0.257)	(0.270)		
N	824	824	824	824
Fixed Effects		+		+

requirements matters for the wage loss during occupational mobility of non-employed workers. The larger the absolute distance in educational requirements between o and o', the larger is the wage loss from mobility. Hence, the distance matrix was constructed as the difference in educational requirements (in years), standardized so that $d_{oo'} \in (0, 1)$.