Embodied Value Chain*

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Abstract

I examine the transfer of customer knowledge by employees as they transition between firms. Leveraging a unique dataset that combines employer-employee matched data with comprehensive firm-to-firm transaction records, I quantify the impact of worker transitions on a recruiting firm's ability to acquire new customers from the networks of the employee's previous employers. By exploiting variations in workers' exposure to different customer portfolios, I demonstrate that customer-specific knowledge significantly increases the likelihood of the recruiting firm forming new business connections by 15% on average, relative to connections without such knowledge transfer. Moreover, the findings reveal that workers transferring valuable network knowledge experience substantial wage premiums, suggesting that the labor market recognizes and rewards the dissemination of such strategic information.

Keywords: Worker mobility, knowledge transfer, firm networks, strategic human capital.

JEL Codes:D22, D85, J24, L14, L25, M51.

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1 Introduction

As employees transition between firms, they carry not only skills but also valuable knowledge about business networks, especially regarding customers and suppliers. This knowledge transfer is so critical that, firms often resort to non-compete agreements to protect their proprietary customer list. However, despite the prevalence of arguments about the transfer of customer knowledge (Posner, 2021), empirically demonstrating this effect has remained a challenge due to data limitations and the difficulty of quantifying knowledge flows.

This study addresses this gap by providing a novel approach to quantify the flow of knowledge about business connections using a rich dataset that combines employer-employee matched data with firm-to-firm transactions. I measure each worker's customer-specific knowledge based on their prior employers' customer portfolios. By exploiting variations in workers' knowledge across different buyers, I examine whether such knowledge increases the likelihood that hiring firms will acquire new customers from those prior portfolios. Specifically, I compare the probability of a recruiting firm forming new connections with customers that were part of the worker's previous employer's network during their tenure, against the probability of connecting with customers acquired after the worker's departure.

The findings reveal that worker knowledge significantly boosts the probability of recruiting firms forming new connections by 15% compared to connections with customers unknown to the transferred workers, highlighting the substantial impact of worker mobility on firms' ability to expand their customer base. Moreover, workers who bring valuable network knowledge to their new firms experience significant wage increases, suggesting that the labor market rewards individuals who possess and transfer such knowledge. Additionally, origin firms face an 8% increase in customer loss due to competition from the recruiting firm. These results underscore how worker mobility reshapes customer networks through the transfer of customer-specific information, accelerates knowledge diffusion, and enhances employee welfare through the transfer of network knowledge.

This study contributes to several strands of literature on strategic management and human capital. It extends the strategic human capital literature by introducing the concept of value chain-specific knowledge, a form of human capital that bridges firm-specific and general knowledge. This concept provides new insights into how firms, particularly young and small ones, develop unique capabilities and network positions. Additionally, it deepens the understanding of knowledge transfer through worker mobility by focusing on relational and network knowledge rather than just technical expertise. The study offers empirical evidence on the transfer of customer relationships through worker mobility, addressing a significant gap in the literature on non-compete agreements and providing a quantifiable measure of previously elusive knowledge flows.

To investigate the impact of worker knowledge on the formation of new network connections, I employ a novel approach to construct treatment and control groups. The flow of information is very difficult to trace in firm-level data. The detailed buyer-seller level data allows me to distinguish between firms that workers were exposed to in their previous roles and those they were not. Consider a hypothetical scenario where a sales manager transitions from a Toyota dealer to a Volkswagen dealer. The firms that the Toyota dealer acquires as customers during the tenure of the manager at the dealer make up the "knowledge treatment" group. To address potential endogeneity concerns, I propose a control group comprising customers acquired by the Toyota dealer after the worker's departure. This ensures that both groups consist of recently acquired customers of the same origin firm, mitigating the influence of factors unrelated to the worker's knowledge.

The empirical strategy compares the probability of the Volkswagen dealer selling to a customer in the treatment group (acquired by the Toyota dealer while the worker was there) versus a customer in the control group (acquired one year after the worker's departure). A higher likelihood of selling to treatment group customers would suggest that the worker's knowledge facilitates the formation of new business connections for the Volkswagen dealer. By carefully constructing these groups, I aim to isolate the causal effect of the worker's previously acquired knowledge on the recruiting firm's ability to establish new network links, while controlling for time-invariant characteristics of the origin firm's customer base.

My findings reveal a significant impact of worker knowledge on network formation in the recruiting firm. Recruiting firms are 15% more likely to establish new network connections with customers in the "knowledge group" compared to the "control group" after hiring workers from their origin firms. This substantial increase highlights the value of customer-specific knowledge transferred through worker mobility and demonstrates its crucial role in expanding the recruiting firm's customer base. This effect is further amplified when entire teams of workers, rather than individuals, transition between firms, underscoring the compounding benefits of collective knowledge transfer. The impact of workers' knowledge is more pronounced for younger and smaller recruiting firms, aligning with the notion that these firms benefit more from additional knowledge due to their limited experience and resources. A validation test on workers in routine occupations with minimal customer interactions, such as technicians or cleaning staff, showed only a modest effect of 3% to 8%. This result supports my argument that the observed outcomes are due to the transfer of customer-specific knowledge through hiring workers with customer information.

Building on my analysis of how hiring firms benefit from employees' networks, I next explore the connection between the networks employees bring and subsequent wage increases for individual contact workers hired by the recruiting firm. My study reveals that workers' wage changes within the recruiting firm are significantly influenced by the potential customer base of the worker's previous employer. Specifically, a one standard deviation increase in this potential customer base results in a 1% rise in wages. These findings, supported by numerous controls and fixed effects, indicate that firms recognize and reward the breadth of knowledge employees bring from their previous roles.

Building on my analysis of how hiring firms benefit from employees' networks, I next explore how the customer knowledge workers bring from their previous employers affects their wages at the recruiting firm. I focus on a worker's "relevant potential customer base", which refers to the number of customers from the worker's previous employer that are relevant to the industries served by the recruiting firm. My study reveals that the size of this customer base significantly influences wage growth at the recruiting firm. Specifically, a one standard deviation increase in the number of relevant potential customers is associated with about a 1% increase in wage growth, representing about a quarter of the average wage growth in the sample. These findings, robust to numerous controls and fixed effects, indicate that firms recognize and reward the breadth and relevance of customer knowledge that employees bring from their previous roles.

Finally, I examine how the departure of contact workers affects the origin firm's customer relationships. While directly measuring this effect is challenging, I instead analyze how competition from the recruiting firm impacts the origin firm's customer links. I analyze the impact of worker mobility on the origin firm's ability to retain customers by comparing the retention rates of customers that are likely to be served by the recruiting firm to those that are not. This comparison is based on the customers' past purchase behaviors. My analysis reveals that customers more aligned with the recruiting firm's market are 4% more likely to be lost by the origin firm, a loss that can be attributed to the direct competition posed by the recruiting firm after it hires workers from the origin firm.

1.1 Related Literature

The strategic management field has long sought to understand the sources of firms' competitive advantage. This paper introduces value chain-specific knowledge as a novel type of human capital, bridging firm-specific and general knowledge. I argue that this knowledge, transferred through worker mobility, critically shapes firm performance and industry dynamics, especially for young and small firms. This study examines the transfer mechanisms and competitive implications of value chain-specific knowledge, addressing gaps in the existing literature. It provides a dual-level analysis: the micro aspect of how workers learn about their employer's network, and the macro analysis of firms' strategic hiring to gain critical knowledge. This approach can explain heterogeneity in firms' knowledge repositories, especially regarding value chains, by focusing on workforce composition and past network connections.

1.1.1 Theoretical Foundations

This study builds upon the foundational theories of the resource-based view (RBV) and knowledge-based view (KBV) of the firm. While the RBV (Barney, 1991; Penrose, 1959) emphasizes unique resource bundles as sources of competitive advantage, and the KBV conceptualizes firms as repositories of knowledge, neither fully explains the origins and dynamics of resource heterogeneity.

Recent work in micro-foundations (Felin and Hesterly, 2007; Abell et al., 2008; Barney and Felin, 2013) have attempted to bridge the connection between individual-level factors and firm-level outcomes. Extending these perspectives, I introduce the concept of value chain-specific knowledge, which offers a new way to understand how firms, particularly young and small ones, develop unique capabilities and network positions. By focusing on the transfer and utilization of customer-specific knowledge through worker mobility, this study sheds light on the processes of resource acquisition and the development of competitive advantage within inter-firm networks.

Strategic Human Capital

The strategic human capital literature addresses a fundamental paradox: while human resources are crucial for competitive advantage, firms don't own their human capital (Coff, 1997). This sparked a debate using the key distinction between general and firm-specific human capital formulated by Becker (1962). Traditionally, firm-specific human capital was seen as the primary source of competitive advantage, as workers couldn't easily transfer this knowledge to other firms.

Campbell et al. (2012a) expanded this framework by positioning firm-specificity as one of several potential mobility frictions. They argue that these frictions, which can work bidirectionally, help explain how firms retain value from their human capital investments. Complementary assets also play a crucial role in this retention (Campbell et al., 2012b). Recent research has begun to challenge the strict dichotomy between firm-specific and general human capital. Ployhart and Moliterno (2011) suggest that general human capital can be combined in unique ways within firms to create firm-specific resources. Groysberg et al. (2008) demonstrate that even star performers may face performance declines when changing firms, highlighting firm-specific components in seemingly portable skills. Moreover, Coff and Raffiee (2015) introduced the concept of "perceived firm-specificity," arguing that subjective assessments of skill transferability can be more impactful than objective firm-specificity.

My concept of value chain-specific knowledge extends this literature by identifying a type of human capital that is neither entirely firm-specific nor fully general. This knowledge, objectively measurable through previous business links and relationships, encompasses customer relationships and value chain insights. Unlike general know-how, it is rival knowledge—if a competitor gains it, the originating firm stands to lose valuable business relationships. By providing a novel and objective measure of this knowledge, my approach advances beyond traditional categorizations, directing attention to the quantifiable network connections that fundamentally drive competitive advantage.

Knowledge Transfer via Worker Mobility

Building on seminal work by Arrow (1962), numerous studies have demonstrated how worker mobility facilitates knowledge transfer across firms (Almeida and Kogut, 1999; Song et al., 2003; Kim, 1997; Zander and Kogut, 1995; Dokko and Rosenkopf, 2010). However, most of this research has focused on technical knowledge. My study expands this view by examining the transfer of relational and network knowledge, which has different competitive implications due to its potentially rival nature.

My work connects to the literature on relational capital (Dyer and Singh, 1998) and social capital (Nahapiet and Ghoshal, 1998; Adler and Kwon, 2002). While these concepts are broader, encompassing structural, relational, and cognitive dimensions, my focus on value chain-specific knowledge provides a more targeted and empirically tractable approach to understanding how firms leverage relationships for competitive advantage.

The concept of boundary spanners highlights the role of individuals in facilitating knowledge flow across organizational boundaries (Tushman and Scanlan, 1981; Aldrich and Herker, 1977). Recent studies have further explored the dynamic role of boundary spanners in various contexts, emphasizing their importance in innovation and inter-organizational collaboration (Marrone, 2010; Burt, 1992; Levina and Vaast, 2005). My work extends this idea by specifically examining how employees with value chain-specific knowledge act as boundary spanners when they move between firms, transferring not just technical knowledge but also relational and network insights. This extension deepens the understanding of boundary spanning by illustrating its importance in the context of value chain-specific knowledge.

Previous research has explored client transfer following worker mobility in service industries (Broschak, 2004; Somaya et al., 2008; Rogan, 2014; Briscoe and Rogan, 2016; Raffiee, 2017; Chondrakis and Sako, 2020). While these studies offer valuable insights, they often face challenges in isolating the causal effect of worker mobility on client transfer, primarily due to endogeneity concerns. Many focus on client loss from the origin firm's perspective, but this approach can conflate the impact of worker departure with other factors influencing client retention. My study advances this research by examining how recruiting firms gain new network connections through strategic hiring and addresses endogeneity with a robust empirical approach. By comparing the likelihood of forming connections with customers familiar to newly hired workers against those unfamiliar, I isolate the effect of worker knowledge transfer. This method reveals a 15% increase in new customer connections directly attributable to worker mobility, offering a clearer causal estimate than previous studies.

Welfare Implications and Policy Considerations

The transfer of value chain-specific knowledge through worker mobility has important implications for industry dynamics and policy. Non-compete agreements have been extensively studied in this context, with research examining their impact on various firm dynamics such as worker mobility, entrepreneurship, innovation, and talent flows (Starr et al., 2021; Marx et al., 2009). Notably, one of the primary arguments put forth in support of non-compete clauses revolves around preventing the transfer of customer lists to competitors through employee departures Posner (2021). However, despite the prevalence of this argument, there is limited empirical evidence on the extent to which customer-specific knowledge is actually transferred through worker mobility. Previous studies, such as Patault and Lenoir (2023), have shown evidence in export markets, but these findings do not generalize to domestic networks due to identification concerns.

In summary, this study contributes to the literature by introducing the concept of value chain-specific knowledge, providing a new method to objectively measure its transfer across firms, and offering empirical evidence on how human capital mobility affects firm networks, performance, and competitive dynamics. These findings enhance our understanding of the strategic implications of employee mobility and the role of customer-specific knowledge in sustaining competitive advantage, especially for young and inexperienced firms seeking to establish their niche in the value chain.

2 Data and Summary Statistics

This study leverages the Enterprise Information System, a comprehensive administrative dataset from Turkey's Ministry of Industry and Technology, covering all formal firms, workers, and transactions in the Turkish economy.[1] Table 1 provides an overview of the dataset's key characteristics, with my analysis primarily drawing on the VAT firm-to-firm transaction data and the employer-employee matched data.

Table 1: Dataset Overview

a. Firm-level data	Number of firms	Employees per firm (median)	Sales (median, USD)	Firm Age (median)
	2,388,491	2	183,000	14
b. Worker-level data	Number of workers	Wages (median, annual USD)	Age (median)	Average Tenure (years)
	27,483,050	8592	32	0.6
c. Transaction-level data	Number of transactions	Number of buyers (median)	Number of suppliers (median)	Duration of Links (median,year)
	415,884,213	5	4	1

Notes: This table provides an overview of the dataset used in the study, which includes firm-level data, worker-level data, and transaction-level data over 2013-2020.

[1]Appendix A provides a detailed description of the data

2.1 Employer-Employee Matched Data

The employer-employee dataset covers all private sector workers from 2012 to 2020. It includes information on wages, occupations, gender, and age. As summarized in Table 1, the dataset encompasses approximately 27 million workers. The median worker age is 32, and the median annual wage is approximately $8,592.

2.2 VAT Transaction Data

In Turkey, as is the case in many countries, the state charges a value-added tax on most goods in the economy. To implement this tax, the government needs to verify the value added by each firm. Firms report their final sales to the government, and for VAT implementation, they report all of their purchases above a threshold of 5,000 TL (approximately $1,500 in 2016) with buyer and seller IDs and the invoice value.

Table 1 summarizes key characteristics of the VAT data. On average, firms have 5 suppliers and 4 customers, with the typical duration of a buyer-seller relationship being approximately one year.

2.3 Sample Construction

To construct the sample, I follow several steps to identify relevant worker movements and their associated firm networks.

2.3.1 Identifying Contact Workers

From the employer-employee matched data, I identify a subset of workers referred to as "contact workers" – those in occupations that require a high degree of customer interaction and knowledge about clients. To identify these customer-facing occupations, I follow the approach of Deming (2017) using the Occupational Information Network (O*NET) data. This dataset assigns scores for various tasks required by each occupation, including customer interaction and routine tasks.

I define contact workers as those in occupations with customer interaction scores more than one standard deviation above the mean and routine scores less than the mean plus one-half standard deviation. This definition aims to capture occupations that involve substantial customer interactions while excluding those that involve repetitive tasks with limited customer knowledge transfer, such as call center operators. Examples of selected contact worker occupations include Public Relations Professionals, Commercial Sales Representatives, and other customer-facing roles. This definition covers approximately 15.6% of all workers in the data.

2.3.2 Worker Mobility Events

I focus on instances where contact workers, about 3.5 million in total, moved between firms. From this group, I select workers who spent at least four quarters at their previous firm, enabling me to identify those who gained knowledge from their former employer. This selection results in a sample of 1.2 million moving workers.

For each worker movement, I identify the recruiting firm and the origin firm for the moving worker. I group workers who moved together from the same origin firm to the same recruiting firm in the same year, defining the mobility event as a tuple of [origin firm, recruiting firm, year].

2.3.3 Relevance and Final Sample

To further refine my sample and focus on the most pertinent instances of knowledge transfer, I introduce the concept of "relevant potential customer" using the VAT dataset. This refinement is crucial due to the sparse nature of the connection matrix in firm networks, where the likelihood of any two firms connecting is generally very low.

When examining knowledge transfer across firms, particularly in the context of supply chains, not all connections are equally relevant. For instance, consider a sales manager moving from a textile company to an apparel company. While the textile company may have a diverse portfolio of customers ranging from automotive to furniture industries, only a subset of these customers may be relevant to the apparel company.

To address this, I define a firm as a "relevant potential customer" for a focal firm if it has purchased from at least one firm in the same industry as the focal firm both one year before and one year after the worker movement event. This definition helps identify customers that are consistently active in the focal firm's industry around the time of worker movement.

This approach significantly reduces the dimensionality of the data. Specifically, "relevant potential customers" constitute only about 10% of the origin firm's total customer base, yet they account for 66% of the sales that the recruiting firm makes to the entire pool of the origin firm's customers. This indicates that while "relevant potential customers" are a small subset, they represent a disproportionately large share of the business relationships that transfer between firms during worker mobility. This shows that, although "relevant potential customers" are a small group, they represent a large share of the business relationships that move between firms when workers change jobs.

The method of using both before and after periods for defining relevance offers several advantages. By requiring customers to have made purchases both before and after the worker movement, I ensure that my estimation is not biased by the timing of a customer's purchasing decisions. This approach helps to isolate the effect of worker knowledge transfer from other factors that might influence customer behavior.

Using this definition, I include worker movements in my final sample if the origin firm acquires at least one "relevant potential customer" for the recruiting firm both before and after the recruitment event. This method allows me to use differences in worker knowledge to understand how knowledge transfers through worker movements

To ensure the robustness of my findings, I test alternative ways to define the relevance. In Section 6.2, I demonstrate that my results hold true regardless of the specific definition of relevance. I show results without any relevance criteria as well, further confirming the observed patterns of knowledge transfer and customer relationship dynamics.

Table 2: Summary Statistics of Worker Movements (Final Sample)

Variable	Median	Mean	SD
Movement from Same Industry	0	0.37	0.48
Movement from Same Province	1	0.63	0.48
Recruiting Firm Employees	57.5	652	3075
Origin Firm Employees	196	1456	4150
Recruiting Firm Buyers	37	223	961
Origin Firm Buyers	86	282.2	958
Relevant Potential Customers	5	10	12
# Movements		297,359	

Notes: This table presents summary statistics for worker movements included in the final sample.

Table 2 presents key characteristics of worker movements in my final sample. Approximately 37.1% of movements occur within the same 2-digit industry, suggesting a substantial degree of industry-specific knowledge transfer. Geographic proximity also plays a significant role, with 63.9% of movements taking place within the same province.

The data reveals a notable size difference between origin and recruiting firms, both in terms of employees and number of buyers. This pattern, where workers tend to move from larger to smaller firms, is a result of my sample construction method. It shows that larger firms are more likely to be origin firms in the sample and to meet my criterion of having acquired new "relevant potential customers" both before and after the recruitment event.

3 Conceptual Framework and Identification Strategy

This section outlines the conceptual framework for identifying the effect of buyer-specific knowledge transfer on new business relationship formation. Consider a simple economy with N buyers and N sellers. A seller s derives profit $\pi_{s,b}$ from selling to buyer b. Sellers activate links (i.e. form business links) when they obtain a positive profit:

$$a_{s,b} = \mathbb{1}[\pi_{s,b} \geq 0],$$

The profit depends on set of observable characteristics X, information $I_{s,b}$ and a stochastic component $\varepsilon(s, b)$.

$$\pi_{s,b} = \beta X_{s,b} + \theta I_{s,b} + \varepsilon_{s,b}, \tag{1}$$

where $I_{s,b}$ is a binary information indicator that decreases the cost of link formation when present ($I_{s,b} = 1$). The parameter θ represents the impact of information on cost reduction. The term $\varepsilon_{s,b}$ captures the inherent suitability of the match between seller s and buyer b, including factors such as prior relationships and alignment of interests.

The primary objective is to measure the impact of recently hired workers' information on link formation, as captured by the parameter θ. If $\varepsilon_{s,b}$ is independent of $I_{s,b}$ conditional on X, I could simply regress $a_{s.b}$ on $I_{s,b}$ to estimate this effect. However, in reality, information and match suitability are likely interdependent, complicating the estimation.

To structure the problem further, consider cases where a seller firm s hires a sales manager to acquire information about b. Initially, $I_{s,b} = 0$, and through hiring, the seller may gain information:

$$I_{s,b} = \begin{cases} 1 & \text{if the hired sales manager transfers knowledge about customer } b \\ 0 & \text{otherwise} \end{cases}$$

The average treatment effect (ATE) is then:

$$\text{ATE} = E[a_{s,b} \mid I_{s,b} = 1] - E[a_{s,b} \mid I_{s,b} = 0]$$

Since I cannot directly observe the counterfactual $E[a_{s,b} \mid I_{s,b} = 0]$ for treated units, I must use a control group. The observed outcomes for treated and control groups can be expressed as:

$$\begin{aligned} E[a_{s,b} \mid I_{s,b} = 1] - E[a_{s,b'} \mid I_{s,b'} = 0] = {} & [E[a_{s,b} \mid I_{s,b} = 1] - E[a_{s,b} \mid I_{s,b} = 0]] \\ & + [E[a_{s,b} \mid I_{s,b} = 0] - E[a_{s,b'} \mid I_{s,b'} = 0]] \end{aligned}$$

For an unbiased ATE estimate, I must assume the second term is zero. However, this assumption likely fails due to the dependence between ε and I. Customers about whom the sales manager has knowledge may be inherently more suitable matches for the seller.

Consider the following regression:

$$a_{s,b,t} = \alpha + \beta I_{s,b,t} + \gamma_s + \delta_b + \eta_t + v_{s,b,t}$$

where γ_s, δ_b, and η_t are seller, buyer, and year fixed effects, respectively. If $E(v_{s,b,t} \mid I) = 0$, I can identify β. The empirical section will explore conditions under which this assumption holds and discuss strategies to address potential violations.

3.1 Worker Mobility and Unobserved Heterogeneity

My analysis focuses on a critical intersection between two distinct but interconnected networks: the labor network, characterized by the flow of workers between firms, and the product network, defined by the flow of goods and services between firms and their customers. When a worker moves from one firm to another, it represents a link in the labor network. However, this movement may be influenced by, and in turn influence, the existing product network connections between firms.

To understand this relationship, I first examine how well the customers of the origin firm (the firm the worker is leaving) align with the recruiting firm's existing network, even before the worker moves. To quantify this alignment, I compare how much the customer bases of the recruiting firm and the origin firm overlap before recruitment. To provide context for this overlap, I also compare it with the overlap between the recruiting firm and various other categories of firms, including random firms chosen based on varying levels of similarity to the recruiting firm (e.g., same industry, same geographic area).

Table 3: Comparison of Overlap of Customers of the Recruiting firm with different set of firms one year before the recruitment

	Mean	**Standard Deviation**
Overlap with Origin Firm	1.52	(6.5)
Overlap with Random Firm	0.01	(0.23)
Overlap with Random Firm in Same 2-Digit Industry	0.12	(1.13)
Overlap with Random Firm in Same Industry	0.2	(1.69)
Overlap with a Random Firm in the Same Industry and Province	0.42	(3.87)

Note: This table presents the mean and standard deviation of the number of customers that overlap between recruiting firms and origin firms, compared to overlaps with random firms in the same industry and/or province. The overlap is measured one year before the recruitment event.

Table 3 presents the results of this analysis. The findings reveal a crucial insight: the customers of the origin firm are not random with respect to the recruiting firm's network. Instead, they show a remarkably high degree of suitability or relevance for the recruiting firm, even before any worker transition takes place.

The overlap between the recruiting firm and the origin firm is significantly higher than with any other category. This overlap is over 100 times greater than with a random firm, and still substantially higher than with firms in the same industry or geographic area.

These results show that the origin firm's customers already align closely with the recruiting firm's network, even before the worker moves. This suggests that the recruiting firm may already be well-positioned to serve the origin firm's customers, regardless of hiring the worker.

The cross-sectional analysis provides a snapshot of the network overlap just before recruitment, highlighting significant differences. However, it is also necessary to investigate the dynamic evolution of this relationship over time. To explore this dynamic aspect, I created a buyer-seller level dataset to track how network overlap changes around worker movements. The event study shows that the probability of sales gradually increases before recruitment, indicating pre-existing and growing network alignment. This reveals the complexity of pinpointing the causal impact of worker knowledge transfer and highlights the need for sophisticated empirical strategies to address the intertwined nature of labor mobility and production networks. Detailed results and regression specifications can be found in the Appendix B.

The endogeneity problem demonstrated in this analysis is not unique to this context. Recent studies using data from Belgium and the Dominican Republic (Komatsua and Dhyne, 2023; Cardoza et al., 2023) have shown that workers strategically direct their job search efforts towards employers connected to their current firm's network, such as suppliers and customers. These findings further underscore the complex interplay between worker movements and inter-firm relationships, reinforcing the importance of careful identification strategies in studying worker mobility and knowledge transfer.

4 Empirical Design

My objective is to measure the causal impact of worker knowledge on the network outcomes of the recruiting firm. For proxying the worker's knowledge on the buyer-seller level, I define the group of knowledge treatment group, which includes customers associated with the worker during their tenure at the origin firm. The important challenge is to find a proper control group where the information of worker is not correlated with the suitability.

4.1 Control Group Using Network Features

To overcome the identification challenges, I exploit the granularity of buyer-seller data along with the timing of the worker's departure: Employees typically possess valuable insights about their firm's customers during their tenure but lack this knowledge for firms that were not customers at that time. This creates variation in worker knowledge that can be leveraged to control for the concern about the correlation between suitability and information. My analysis focuses on how the recruiting firm forms new links with two distinct sets of customers from the worker's previous employer (the origin firm):

- **Knowledge Treatment Group**: The set of customers that the origin firm acquired exactly one year before the focal worker's transition to the recruiting firm.

- **Control Group**: The set of customers that the origin firm acquired exactly one year after the focal worker's transition to the recruiting firm. [2]

The one-year cutoff is chosen to ensure a clear distinction between customers the worker likely knew and those they didn't, while maintaining comparability between the groups. The Knowledge Treatment and Control Groups are designed such that both groups consist of customers relevant to the same recruiting firm, acquired from the same industry within a narrow timeframe. The key difference between the two groups is that the Knowledge Treatment Group consists of customers acquired before recruitment, whom the worker likely knew, while the Control Group consists of customers acquired after recruitment, whom the worker did not know.

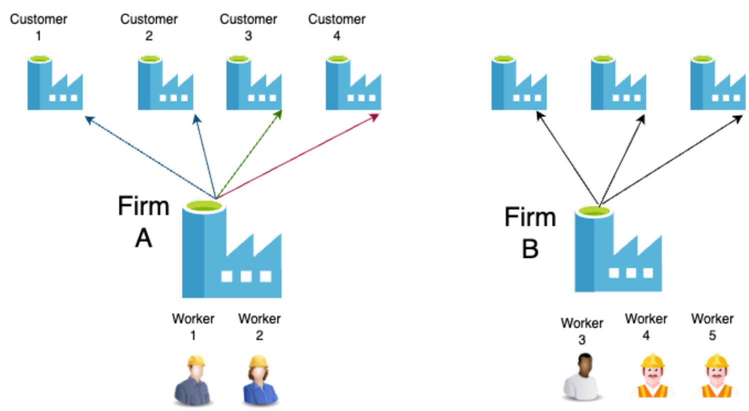

Figure 1: Diagram illustrating a typical scenario involving a recruiting firm A and an origin firm B after period t_i, the year worker 3 has moved to firm B. In the diagram, customers 1 and 2 are existing customers of the origin firm acquired before worker 3's tenure. Customer 3, who was acquired by the origin firm during worker 3's tenure (period t_{i-1}), belongs to the Knowledge Treatment Group. Customer 4, acquired one year post-recruitment (period t_{i+1}), belongs to the Control Group.

Section 3.1 shows that the suitability between customers of the origin firm and recruiting firm is generally high and follows a time-trend, accelerating before recruitment. This suitability would introduce bias if not properly controlled. By using recently acquired customers of the origin firm for both treatment and control groups, the analysis assumes that any inherent suitability is comparable, allowing for the effect of knowledge transfer on link formation to be isolated. This approach

[2] I tested different control group thresholds by varying the time window from one to four years post-transition, while keeping the treatment group constant in section C.3. The results show that the knowledge transfer effect is stable for one-year and two-year cutoffs, indicating that the main findings are robust to small variations in the control group definition. As the cutoff extends to three and four years, the coefficients increase, suggesting a stronger effect over time, although this may also capture other time-varying factors.

mitigates concerns that the differences in link formation are solely due to suitability rather than knowledge transfer.

This approach allows me to more accurately estimate θ in equation 1, the key parameter of interest in my theoretical model. By comparing customers acquired during the worker's tenure to those acquired after their departure, I create a setting where differences in link formation probabilities can be more confidently attributed to the effect of worker knowledge (θ) rather than underlying match suitability ($\varepsilon_{s,b}$). It also effectively controls for the origin firm's network position and any time-invariant firm characteristics that may influence both customer acquisitions and worker hiring decisions.

The validity of this approach rests on the assumption that, in the absence of worker knowledge transfer, the recruiting firm's propensity to form new links with the treatment and control groups would follow similar trends. This assumption is plausible because both groups, on average, would have similar suitability with the recruiting firm, as they were all recent customers of the origin firm.

4.1.1 Main Regression

To evaluate the effect of this knowledge transfer, I estimate the following regression comparing the post-recruitment link formation probability:

$$a_{s,b,t} = \alpha + \beta \mathbb{1}[(s,b) \in \text{Knowledge Treatment}] + \gamma_s + \delta_b + \eta_t + v_{s,b,t} \tag{2}$$

Here, $a_{s,b,t}$ is a binary variable that equals 1 if the recruiting firm s (the seller) sells to firm b (the buyer) in year (t), and 0 otherwise. $\mathbb{1}[(s,b) \in \text{Knowledge Treatment}]$ is a binary indicator that equals 1 if the customer b belongs to the Knowledge Treatment Group for the recruiting firm s, and 0 if it belongs to the Control Group, $v_{s,b,t}$ is the residual.

To reiterate, the data construction process takes each recruitment event and forms pairs consisting of the recruiting firm (seller) and potential customers (buyers), categorized as either the Knowledge Treatment Group or the Control Group. Each (s, b) pair is tracked for three years after recruitment, with annual records indicating whether the recruiting firm sells to these customers. This setup directly compares the probability of the recruiting firm forming links with customers in the Knowledge Treatment Group versus those in the Control Group. Fixed effects are applied to control for time-invariant characteristics of sellers and buyers, as well as time-variant factors such as demand conditions, ensuring that the analysis isolates the effect of knowledge treatment on link formation. The coefficient of interest, β, captures the differential effect of the worker's knowledge on the likelihood that the recruiting firm forms a new connection with a customer in the Knowledge Treatment Group, relative to a customer in the Control Group, following the worker's transition. A positive and statistically significant estimate of β would support the hypothesis that the worker's knowledge facilitates the formation of new buyer-seller connections.

Table 4: The Effect of Knowledge on Probability of Link for Contact Workers

	(1) Link Formation	(2) Link Formation	(3) Link Formation	(4) Link Formation	(5) Link Formation	(6) Link Formation	(7) Link Formation
Knowledge Treatment	0.146***	0.147***	0.090***	0.133***	0.101***	0.148***	0.150***
	(0.005)	(0.033)	(0.024)	(0.021)	(0.019)	(0.021)	(0.021)
Year FEs		Yes	Yes	Yes	Yes	Yes	Yes
Seller FEs			Yes		Yes	Yes	Yes
Buyer FEs				Yes	Yes	Yes	Yes
BuyerYear FEs						Yes	Yes
SellerYear FEs							Yes
Observations	16,348,242	16,348,242	16,348,242	16,348,242	16,348,242	16,348,242	16,348,242
R^2	0.000	0.040	0.081	0.113	0.193	0.209	0.209

Notes: This table shows the impact of recruiting workers with customer-specific knowledge on the probability of forming new business connections. The "Knowledge Treatment" variable indicates whether the customer was acquired during the worker's tenure at the origin firm. The sample includes treatment and control groups, where the control group consists of customers acquired by the origin firm after the worker's departure. The data is at the buyer-seller-year level, with the selling firm being the recruiting firm, and includes only post-recruitment years. It compares the probability of the recruiting firm acquiring customers from the knowledge treatment group versus the control group. Values are normalized using the mean link formation probability, meaning the results represent the increase in probability relative to the average probability of link formation. The sample size of approximately 16,348,242 observations reflects the structure of the data: with around 300,000 worker movements, an average of 18 relevant customers per movement(both treatment and control), and three post-recruitment years (300,000 * 18 * 3 ≈ 16,200,000). Standard errors are clustered around 4-digit NACE2 code.

Table 4 presents the results of this regression with various fixed effects specifications. The values are normalized using the mean link formation probability, meaning the results represent the increase in probability relative to the average probability of link formation. Therefore, the coefficients should be interpreted as the increase in the probability of sales to the treatment group relative to the probability of sales to the control group.

Across all specifications, the treatment effect β is positive and statistically significant at the 1% level, providing strong evidence that worker knowledge facilitates the formation of new buyer-seller connections. In the baseline specification (column 1) the results suggest that the probability of forming a new connection with a customer in the Knowledge Treatment Group is 14.6 percentage points higher than with a customer in the Control Group.

As I progressively add fixed effects, the treatment effect remains substantial and statistically significant. This indicates that the observed effect is not driven by year-specific shocks, time-invariant seller characteristics, or time-invariant buyer characteristics. In my most stringent specification (column 7), which includes seller-year and buyer-year fixed effects, the treatment effect is 15.0 percentage points. These fixed effects control for time-invariant characteristics of sellers and buyers that could affect my estimates, as well as time-variant characteristics such as demand conditions. Specifically, if the treatment and control group buyers have different demand conditions around the year of recruitment, buyer-year fixed effects will account for this potential confounding factor.

In summary, my results provide strong evidence that worker knowledge significantly increases the probability of new link formation, with a magnitude of around 15 percentage points. This effect is robust to a variety of fixed effects specifications, suggesting a causal relationship between worker knowledge transfer and the expansion of firm networks.

It's worth noting that I have sufficient variation in the data to implement these stringent fixed effects. A typical recruiting firm is involved in around 3 movements (2.95) and has around 5 potentially relevant customers. Similarly, a typical buyer is involved in around 30 different movements. Since the movements span a 6-year period from 2013 to 2019, I have enough variation to justify the use of buyer-year and seller-year fixed effects.

Finally, to ensure that the observed differences are not driven by systematic dissimilarities between the knowledge treatment group and the control group, it is crucial to examine the balance of firm characteristics across the two groups. Table 15 in the appendix presents the results of a balance test, comparing various attributes of firms in the treatment and control groups. The findings reveal that firms in the control group are slightly larger, with 2% more suppliers and

4% more sales on average. Any potential advantage is more likely to favor the control group reinforces the conservative nature of the estimates, as it would work against finding a significant effect of worker knowledge on the formation of new buyer-seller links, nevertheless the empirical specification should correct any difference between these groups which is addressed by the fixed effects.

4.2 Matching on Observables

As an alternative approach, I employ a matching strategy based on observable characteristics of the buyers. This method aims to create a control group that closely resembles the treatment group in terms of observable features, but does not receive the knowledge transfer from the recruited worker. The process begins by identifying the treatment pairs, consisting of the recruiting firm as the seller and the "relevant potential customers" of the origin firm acquired one year before the recruitment as buyers. For each customer in these treatment pairs, I then match another firm that is also "relevant potential", operates in the same industry as the treatment buyer, and closely matches the treatment buyer in terms of observable characteristics including sales, employment, productivity, and the number of buyers and sellers. This matching is performed within the subset of firms that are both "relevant potential" and within the same industry as the customer, using the aforementioned characteristics as matching criteria. The goal of this approach is to construct a control group that mirrors the treatment group in terms of observable characteristics, but crucially, has not been exposed to the potential knowledge transfer from the recruited worker. I then employ the same regression specified in Equation 2, now utilizing this matched control group. This allows for a comparison between the results obtained from the network-based approach and those from this matching on observables strategy, providing insight into the robustness of the observed effects of worker knowledge transfer.

Table 5: The Effect of Knowledge with Matched Control Group and Network Control Group for Contact Workers

	Matched Control		Network Control	
	(1)	(2)	(3)	(4)
	Link Formation	Link Formation	Link Formation	Link Formation
Knowledge Treatment	2.198***	1.943***	0.146***	0.150***
	(0.013)	(0.168)	(0.005)	(0.021)
Year FEs		Yes		Yes
Seller FEs		Yes		Yes
Buyer FEs		Yes		Yes
BuyerYear FEs		Yes		Yes
SellerYear FEs		Yes		Yes
Observations	15,920,274	15,920,274	16,348,242	16,348,242
R^2	0.002	0.200	0.000	0.209

Notes: This table compares the estimated effect of worker knowledge transfer on the probability of forming new business connections using two different control group approaches. The treatment group consists of customers acquired by the origin firm during the worker's tenure. In the network control group, the control consists of customers acquired by the origin firm after the worker's departure. In the matched control group, the control group is based on observable characteristics such as sales and employment. The data is at the buyer-seller-year level, with the selling firm being the recruiting firm, and includes only post-recruitment years.Values are normalized using the mean link formation dummy. Standard errors are clustered around 4-digit NACE2 code.

Table 5 presents the estimation results with the matching controls alongside my preferred design of network controls. Across all fixed effects specifications, the matching control yields a coefficient on the knowledge group of more than 1.9, indicating at least a 190% increase in the sales probability for the treatment group compared to the control group. This contrasts sharply with the 15% increase estimated using the network control approach. This dramatic difference highlights a significant issue with the matching control group setup, which fails to adequately account for the underlying correlation between information and suitability, represented by $\varepsilon_{s,b}$.

The substantial bias in estimating the treatment effect arises because customers known to the recruited worker inherently have higher $\varepsilon_{s,b}$ values, indicating they are more suited for forming new links compared to control group customers matched solely on observables. This reflects a fundamental insight: the flow of people and goods often follow similar trajectories, meaning the origin firm and its customers are inherently more suited to the recruiting firm in terms of market fit, driving the exceptionally high results in the matching approach.

This misalignment underscores the necessity of properly addressing the suitability factor $\varepsilon_{s,b}$ in control group selection. Simply matching on observable characteristics within the same industry fails to capture the intertwined nature of labor networks and production networks. Knowledge flows through channels one cannot directly observe, echoing Samuelson's notion of knowledge being "in the air."

The interconnectedness can be partly explained by a community around the firm, comprising individuals linked through various relationships: past or current coworkers, supplier-customer interactions, job applications, business organizations, industry conferences, and other social ties. Knowledge disseminates through these social relationships, making it challenging to isolate specific knowledge transfer attributed to individual workers. Observing a firm hiring from another firm provides insights into the suitability between the clients of the origin firm and the recruiting firm, increasing the potential for knowledge flow in ways not directly observable.

Consequently, any study examining the effect of recruitment must account for this intertwined nature of networks. Failing to do so can lead to easily finding positive results that cannot be causally attributed to the recruitment of a specific worker. This underscores the importance of careful control group selection and the need for methods that can disentangle the effects of individual worker knowledge transfer from broader network suitability.

4.3 Validation Test on Routine Workers

Having demonstrated that contact workers transfer critical knowledge about customers, I now validate these findings by investigating knowledge transfer among workers expected to have less customer-specific knowledge. I examine workers who primarily perform routine tasks, such as technicians or cleaning staff, whose roles are typically less customer-facing. To maintain consistency, I apply the same regression model (Equation 2) to the movements of routine workers, focusing on the network control approach.

Table 6 presents the results of this analysis. When using network controls, the effects for routine workers are substantially muted. Without fixed effects, the impact is around 3%, and even with the most comprehensive set of fixed effects, it only reaches about 8%[3].

Table 6: The Effect of Knowledge with Network Control Group for **Contact and Routine Workers**

	Contact Workers (Baseline)		**Routine Workers**	
	(1)	(2)	(3)	(4)
	Link Formation	Link Formation	Link Formation	Link Formation
Knowledge Treatment	0.146***	0.150***	0.029***	0.082***
	(0.005)	(0.021)	(0.005)	(0.011)
Year FEs		Yes		Yes
Seller FEs		Yes		Yes
Buyer FEs		Yes		Yes
BuyerYear FEs		Yes		Yes
SellerYear FEs		Yes		Yes
Observations	16,348,242	16,348,242	15,233,175	15,233,175
R^2	0.00	0.209	0.000	0.157

Notes: This table presents the results of the knowledge transfer effects using network control groups for both contact and routine workers. Contact workers are those who are expected to have significant customer-specific knowledge, while routine workers are expected to have less customer-specific knowledge. The network control group includes customers acquired by the origin firm after the worker's departure. The data is at the buyer-seller-year level, with the selling firm being the recruiting firm, and includes only post-recruitment years. Values are normalized using the mean link formation dummy. Standard errors are clustered around 4-digit NACE2 code.

These results lead to two important conclusions. First, they confirm a significant difference in knowledge transfer between contact workers and routine workers. Second, they provide further evidence that network controls offer a more accurate estimation of the effects of worker movements, as they can better account for the specific knowledge transfer.

While there is some evidence of knowledge transfer by routine workers, the effect is modest and substantially smaller than that observed for contact workers. The impact of routine workers' knowledge on the recruiting firm's ability to form new customer connections is less than 8%, considerably lower than the 15% effect observed for contact workers.

This validation test strengthens the main findings of the study. It demonstrates that the observed effects for contact workers are indeed attributable to their customer-specific knowledge rather than being an artifact of worker movement in general. The stark contrast between the results for contact

[3]The matching control exercise, not shown here, continues to yield high effects, ranging from 180% to 200%, similar to the inflated results observed with contact workers. This overestimation suggests that matching on observables alone does not adequately account for the underlying correlation between information and suitability.

workers and routine workers underscores the unique value of customer-facing roles in transferring valuable network knowledge across firms.

These findings reinforce my argument that the significant effects observed for contact workers are indeed attributable to the transfer of customer-specific knowledge facilitated by their customer-facing roles. The modest and inconsistent effects for routine workers, who are less likely to possess such knowledge, serve as a falsification test, validating my main results.

4.4 Factors Influencing the Strength of Knowledge Transfer

To further investigate the factors that influence the strength of knowledge transfer, I interact several variables with the treatment variable. In my preferred specification, I add the variable itself and its interaction with the treatment variable to the main regression equation:

$$\begin{aligned} a_{s,b,t} = \alpha + \beta \mathbb{1}[(s,b) \in \text{Knowledge Treatment}] + \lambda(\mathbb{1}[s, b \in \text{Knowledge Treatment}] \times X_{s,b,t}) \\ + \zeta X_{s.b,t} + \gamma_s + \delta_b + \eta_t + \nu_{s,b,t} \end{aligned} \tag{3}$$

Here, $X_{s,b,t}$ represents the factor being investigated (e.g., number of workers, firm age), and λ captures the differential effect of the treatment across different levels of this factor. The coefficients of these interaction terms (λ) are provided in Figure 2.

First, I find that the number of workers transferring from the origin firm to the recruiting firm has a significant effect, which supports the idea that having more employees involved enhances the strength of information transfer. Importantly, the effect is more pronounced when the recruiting firm is younger and smaller. Since these firms are relatively inexperienced in the network, the transferred knowledge carries more importance for them, potentially giving them a competitive edge in forming new connections.

Additionally, I observe a higher effect when the origin firm is smaller, suggesting that the knowledge of contact workers about customers might be more concentrated in smaller origin

Figure 2: The Effect of Different Factors on the Impact of Knowledge Transfer.

Notes: This figure illustrates the effect of various factors on the impact of worker knowledge transfer on the probability of forming new business connections. The main regression compares the knowledge treatment group with the network control group while adding variables and their interactions with the knowledge treatment. The coefficients shown represent the interaction terms, denoted as λ, from Equation 2, capturing the interaction of each variable with the knowledge treatment. Standard errors are clustered around the 4-digit NACE2 code.

companies. This finding implies that workers from smaller firms may have more intimate knowledge of their customers, which can be particularly valuable when transferred to the recruiting firm.

Interestingly, my analysis reveals that as the tenure of the worker at the origin firm increases, the effect of knowledge transfer on network formation tends to decrease. This finding may appear counterintuitive, as one might expect workers with longer tenures to have accumulated more valuable customer knowledge over time. However, a plausible explanation lies in the nature of firm-specific human capital accumulation. Workers with extended tenures at their origin firms may have developed more specialized knowledge and skills that are less transferable to other firms, resulting in a diminished impact on the recruiting firm's ability to leverage their customer network knowledge.

Furthermore, the effect of knowledge transfer is amplified when the worker transitions between firms within the same two-digit industry. In such cases, the impact on network formation triples, underscoring the heightened salience of knowledge flows between direct competitors. This observation highlights the strategic importance of worker mobility within industries, as it facilitates the diffusion of customer-specific knowledge and potentially reshapes competitive dynamics through the expansion of customer networks.

5 Ripple Effects of Knowledge Transfer: Workers and Origin Firms

5.1 Impact of Knowledge Breadth on Wage Growth

Having established knowledge transfer and its use by recruiting firms, I now examine how this knowledge is valued in the labor market. If firms recognize the value of customer-specific knowledge, it should be reflected in workers' compensation. This section investigates whether the breadth of a worker's knowledge influences their wage growth when transitioning to a new firm.

5.1.1 Measurement and Empirical Strategy

To quantify the breadth of a worker's knowledge, I use the number of "relevant potential customers" at the origin firm during the worker's tenure. This measure is directional, as it depends on the recruiting firm's industry. Note that a firm is considered "relevant potential customer" if it was a customer of at least one firm in the recruiting firm's industry. Consequently, a worker from a given origin firm may have different knowledge breadth scores depending on the industry of the recruiting firm.

Unlike in previous sections, I do not restrict my analysis to recently acquired customers. Instead, I consider the entire customer base of the origin firm to provide a more comprehensive view of the worker's accumulated knowledge. Summary statistics for key variables in the dataset are in Table 14 in the appendix.

To analyze the impact of knowledge breadth on wage growth, I employ the following regression model:

$$\Delta\log(w^{r,o}_{i,t}) = \beta\log(\text{RelevantCustomers}^{o}_{i,t-1})+\gamma\log(\text{TotalCustomers}^{o}_{i,t-1})+\text{Controls}+\text{FE}+\epsilon^{r,o}_{i,t} \quad (4)$$

Where $\Delta\log(w)^{or}_{it}$ is the log difference in daily wage between the recruiting firm r and the origin firm o for worker i at time t. $\text{RelevantCustomers}^{o}_{i,(t-1)}$ is the number of "relevant potential customers" at the origin firm, and $\text{TotalCustomers}^{o}_{i,(t-1)}$ is the total customer base of the origin firm. Controls include firm-level characteristics (e.g., assets, financial ratios) for both recruiting and origin firms, as well as worker-level attributes (e.g., age, gender, occupation). FE represents various fixed effects, including year, recruiting firm, and origin firm fixed effects.

5.1.2 Results and Interpretation

Table 7: Effect of Breath of Worker's Knowledge on Wage Growth

	(1) ΔWage	(2) ΔWage	(3) ΔWage
Relevant Customer Base(log)	0.006***	0.007***	0.009***
	(0.001)	(0.001)	(0.001)
Total Customer Base(log)		-0.003***	-0.003***
		(0.001)	(0.003)
Firm Controls	Yes	Yes	Yes
Origin Firm Controls	Yes	Yes	Yes
Worker Controls	Yes	Yes	Yes
Year FE's	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Origin Firm FE's			Yes
Observations	761,299	761,299	761,299
R^2	0.33	0.33	0.42
Mean ΔWage		0.05	

Notes: This table examines how the breadth of a worker's knowledge impacts on wage growth after moving to a new firm. The sample includes only contact workers who move from the origin firm to the recruiting firm. The data is at the worker-year level, focusing on the years spent at the recruiting firm. The dependent variable is the log difference between the actual wage at the recruiting firm and the last wage at the origin firm. The relevant customer base is the number of customers of the origin firm that are relevant to the recruiting firm, normalized by employment. The wage variable is the real daily wage. Standard errors are clustered around 4-digit NACE2 code.

Table 7 presents the results of the regression analysis. The findings demonstrate a consistent positive relationship between the breadth of a worker's relevant customer knowledge and their wage growth upon transitioning to a new firm.

In the baseline specification (column 1), the coefficient on the log of relevant customers is 0.006, significant at the 1% level. This effect remains robust when controlling for the total customer base of the origin firm (column 2) and including origin firm fixed effects (column 3).

The most comprehensive model (column 3) shows the strongest results. The coefficient on the relevant customer base is 0.009, significant at the 1% level. This implies that a one standard deviation increase in the log of relevant customers (1.4) is associated with a 1.26% increase in wage growth (0.009 * 1.4). Given that the mean wage growth in the sample is 5%, this effect represents about a quarter of the average wage growth, indicating its economic significance. The total customer base of the origin firm shows a small negative effect (-0.003) across specifications. This suggests that wage growth is driven by the relevance of the worker's customer network to the recruiting firm's industry, not by the overall size of the network.

The robustness of these results to the inclusion of various controls and fixed effects, particularly the origin firm fixed effects, strengthens their validity. The persistent effect indicates that the observed relationship is not primarily driven by unobserved characteristics of the origin firms or general differences in firm size or industry.

These findings show that firms recognize and reward the customer-specific knowledge that workers bring from their previous employers. The magnitude of the effect suggests that this form of human capital is valued in the labor market for customer-facing roles.

Moreover, the results point to a nuanced view of valuable human capital. The positive effect of relevant customers, coupled with the negative effect of total customers, suggests that firms distinguish between different types of customer knowledge in their valuation of workers. They place a premium on knowledge that aligns with their own customer base and industry, rather than broad but potentially less relevant customer exposure.

In summary, these results establish a link between the breadth of a worker's relevant customer knowledge and their wage growth when moving between firms. This relationship persists across various specifications and controls, providing evidence of the importance of customer-specific knowledge in the labor market.

5.2 Effects on Origin Firm

An important aspect of employee mobility and the associated transfer of knowledge is its impact on the origin firm. Measuring the effect of worker departures on client loss for the origin firm is difficult due to confounding factors and the challenge of isolating the direct impact of the employee's exit. Specifically, it is hard to demonstrate information leakage, as much of the critical knowledge may still be retained within the firm through existing documentation and the collective experience of remaining employees.

A feasible approach to this problem is to compare customer groups that are affected by competition due to recruitment with those that are not. Using granular buyer-seller data, I can identify customer relationships that are likely to face greater competition from the recruiting firm after it hires a worker and compare them with relationships less affected by this dynamic. This approach clearly highlights the impact of competition stemming from recruitment. For this analysis, I use the concept of "relevant potential customers" introduced earlier, which identifies customers most likely to be targeted by the recruiting company.

Before delving into details, it's important to note that relevant potential firms are more likely to be served by the recruiting firm. In fact, 66% of sales by the recruiting firm occur within this pool of customers. Therefore, if I can detect an increase in attrition of these customers after the recruitment event, it could be attributed to the departure of the worker and subsequent competition from the recruiting firm.

To establish a suitable control group, I need a set of customers that are also potentially relevant for some firms. The best candidate for this is the origin firm itself. This allows me to compare the attrition rates of relevant potential customers for the recruiting firm with the attrition rates of relevant potential customers for the origin firm. However, since I use the industry of the focal firm to define relevancy, the sample should only include recruiting and origin firms that are not in the same 4-digit industry.

My previous definition of network relevancy used future sales data, which is problematic in this context because I have two different focal points (recruiting and origin firms), and their future histories may affect the attrition differentially. To address this, I introduce a new concept of pre-sample network relevancy:

Pre-sample Relevance: A customer is considered a "relevant potential customer" for a focal firm if it has purchased from at least one firm in the same industry as the focal firm in the year before the start of the sample period. This definition eliminates the possibility of future sales influencing the categorization of "relevant potential customer", which could introduce bias when examining the effect of competition on customer attrition.

This setup allows for a difference-in-differences analysis. The key assumption is that, in the absence of worker departure, the link attrition probability of the origin firm for these different groups would be similar. While there could be ways this assumption might not hold (e.g., if past histories of these groups affect attrition differentially), this approach can provide valuable insights into customer attrition due to increased competition for the origin firm.

To analyze the competitive effects, I compare two groups of customers:

1. Treatment group: Customers "relevant potential" for the recruiting firm
2. Control group: Customers "relevant potential" for the origin firm, but not for the recruiting firm

I use a difference-in-differences setup, regressing customer attrition on the relevance treatment. The regression equation is:

$$\Delta a_{s,b,t} = \beta_1 \text{Post} + \beta_2 \mathbb{1}[(s,b) \in \text{RelevanceTreatment}] + \beta_3(\text{Post} \times \mathbb{1}[(s,b) \in \text{RelevanceTreatment}]) + \text{seller}_s + \text{buyer}_b + \text{year}_t + \epsilon_{s,b,t} \tag{5}$$

The analysis incorporates various fixed effects to control for unobserved heterogeneity and provide robust estimates. Year fixed effects account for time-specific factors, while buyer and buyer-seller pair fixed effects control for unique characteristics of the customers and their relationships with firms. This ensures that the results are not confounded by broader economic trends or stable, unobserved differences.

Table 8: The Effect of Worker Departure on Customer Attrition by the Origin Firm

	(1) ΔLink Formation	(2) ΔLink Formation	(3) ΔLink Formation
Post	-0.641***	-1.035***	-1.504***
	(0.000)	(0.016)	(0.024)
Relevance Treatment	0.022***	0.011***	–
	(0.003)	(0.003)	
Post × Relevance Treatment	-0.026***	-0.021***	-0.017***
	(0.001)	(0.005)	(0.004)
Year FEs	No	Yes	Yes
Seller FEs	No	No	No
Buyer FEs	No	Yes	No
Buyer-Seller Pair FEs	No	No	Yes
Observations	14,898,345	14,898,345	14,898,345
R-squared	0.280	0.362	0.463

Notes: This table shows the impact of worker departure on customer attrition for origin firms. The "Relevance Treatment" variable indicates whether a customer is relevant potential for the recruiting firm. The "Post" variable captures the period after the worker's recruitment. The interaction term "Post × Relevance Treatment" measures the effect of being a relevant customer after the recruitment event. The analysis uses a difference-in-differences approach, comparing the probability of customer attrition between treatment and control groups. The sample includes customers who were relevant to either the origin firm or the recruiting firm, focusing on periods around worker recruitment events. The data is structured at the buyer-seller-year level, ensuring that all events occur after the pre-sample relevance is established. This approach helps isolate the effect of worker mobility on customer attrition. Standard errors are clustered around NACE2 codes.

The analysis, shown in Table 8, reveals that after recruitment, there is a 2% increase in the likelihood of customer loss for "relevant potential customers" of the recruiting firm. To put this into perspective, the average annual customer attrition rate in the sample is approximately 52%. Therefore, this 2% increase translates to a 4% relative rise in the risk of losing customers. In Table 8, the results are shown with different levels of fixed effects: the first column presents the baseline, while the subsequent columns incorporate year and buyer-seller relationship effects, ensuring the robustness of the observed impact.

These findings suggest that knowledge transfer through employee mobility creates significant competitive pressures for origin firms, especially among customers who are likely to be targeted by the recruiting firm. This analysis enhances our understanding of how employee mobility influences competition, highlighting the need for origin firms to manage employee transitions carefully and protect valuable customer relationships.

6 Robustness Analysis and Quantification

6.1 Robustness: Placebo Test with Random Sellers

To further validate my main findings and rule out potential confounding factors, I conduct a placebo test by replacing the actual recruiting firm with a randomly selected firm from the same industry. This approach allows me to examine whether the observed increase in link formation probability is genuinely attributable to worker knowledge transfer or if it could be explained by inherent characteristics of the two groups or any unobserved heterogeneity.

I maintain the structure of the knowledge treatment and control groups as in my main analysis but substitute the recruiting firm with a random firm from the same industry that did not recruit the worker in question. This placebo test enables me to assess whether any intrinsic factors related to these customer groups, rather than the specific knowledge transferred by the recruited worker, drive the observed effects.

I estimate Equation 2 using this random firm in place of the actual recruiting firm. Table 9 presents the results of this placebo test.

Table 9: The Effect of Knowledge on Probability of Link for Random Seller

	(1) Link Formation	(2) Link Formation	(3) Link Formation	(4) Link Formation	(5) Link Formation	(6) Link Formation	(7) Link Formation
Knowledge Treatment	-0.094***	-0.093**	-0.062*	-0.045	-0.026	0.008	0.015
	(0.024)	(0.041)	(0.038)	(0.043)	(0.042)	(0.039)	(0.039)
Year FEs		Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs			Yes		Yes	Yes	Yes
Buyer FEs				Yes	Yes	Yes	Yes
BuyerYear FEs						Yes	Yes
SellerYear FEs							Yes
Observations	14,511,518	14,511,518	14,511,518	14,511,518	14,511,518	14,511,518	14,511,518
R^2	0.000	0.0002	0.035	0.012	0.048	0.069	0.091

Notes: This table presents a placebo test to examine whether the observed increase in link formation is specific to the recruiting firm or if it could be attributed to general industry dynamics. The "Knowledge Treatment" variable indicates whether a customer is part of the knowledge treatment group. In this analysis, the recruiting firm is replaced by a random firm within the same industry that did not recruit the worker. The sample includes treatment and control groups: the treatment group consists of customers relevant to the random industry firm, while the control group consists of customers relevant only to the origin firm. The data is at the buyer-seller-year level, and only post-recruitment years are considered. This setup tests whether the knowledge treatment group experiences a boost in link formation independent of actual recruitment. Values are normalized using the mean link formation probability, representing the increase in probability relative to the average probability of link formation. Standard errors are clustered around 4-digit NACE2 codes.

The results of my placebo test provide strong support for the validity of my main findings. In the most rigorous specification, which includes both buyer-year and seller-year fixed effects (Column 7), I find no statistically significant increase in the probability of link formation between the random firm and the knowledge treatment group. This contrasts sharply with my main results, where I observed a significant positive effect for the actual recruiting firm.

Interestingly, in the specification without fixed effects (Column 1), I observe a negative and statistically significant coefficient, indicating that random firms are actually more likely to connect with the control group rather than the knowledge treatment group. This effect, however, dissipates as I introduce various fixed effects, suggesting that any differences between the groups unrelated to worker knowledge transfer may actually favor the control group.

These findings alleviate concerns about spurious effects in the main analysis. The fact that random firms do not show increased connections with the knowledge treatment group—and may even prefer the control group in some specifications—enhances confidence that the observed effects in the main analysis are indeed due to the transfer of worker-specific knowledge.

In conclusion, this placebo test provides strong evidence that the increased probability of link formation observed in the main analysis is genuinely attributable to the specific knowledge transferred by recruited workers, rather than to any inherent characteristics of the customer groups or industry-wide dynamics. This robustness check reinforces the validity and specificity of the findings on the role of worker mobility in facilitating inter-firm knowledge transfer and network formation.

6.2 Robustness to Alternative Definitions of Relevant Potential Customers

To further assess the robustness of my results, I examined the impact of my sample construction, particularly the definition of relavance. I tested three scenarios:

1. Baseline definition: A firm is considered "relevant potential customer" for a focal firm if it has purchased from at least one firm in the same industry as the focal firm both one year before and one year after the worker movement event.
2. Pre-sample Relavance: A firm is considered "relevant potential customer" for a focal firm if it has purchased from at least one firm in the same industry as the focal firm in 2013, the year before recruitment events begin.
3. Full sample: No relavance restrictions applied.

Table 10 presents the results for these scenarios.

Table 10: The Effect of Knowledge with Baseline, Relevance 2, and All Sample for Contact Workers

	Baseline		Pre-sample Relevance		All Sample	
	Link Formation	Link Formation	Link Formation	Link Formation	Link Formation	Link Formation
Knowledge Treatment	0.146***	0.150***	0.115***	0.150***	0.040***	0.105***
	(0.005)	(0.021)	(0.004)	(0.022)	(0.003)	(0.021)
Year FEs		Yes		Yes		Yes
Seller FEs		Yes		Yes		Yes
Buyer FEs		Yes		Yes		Yes
BuyerYear FEs		Yes		Yes		Yes
SellerYear FEs		Yes		Yes		Yes
Observations	16,348,242	16,348,242	21,940,621	21,940,621	71,551,301	71,551,301
R^2	0.000	0.209	0.000	0.195	0.000	0.093

Notes: This table presents the results of our main analysis under different "relevant potential customer" definitions. We consider three scenarios: (1) Baseline Relevance, where a customer is relevant if it purchased from the industry one year before and after the worker movement; (2) Pre-sample Relevance, where relevance is determined based on purchases in the year before our sample period; and (3) Full Sample, with no relevance restrictions. The treatment group consists of customers acquired by the origin firm during the worker's tenure. The data is at the buyer-seller-year level, with the selling firm being the recruiting firm, and includes only post-recruitment years. Values are normalized using the mean link formation dummy. Standard errors are clustered around 4-digit NACE2 code.

The results remain consistent across the baseline and pre-sample relavance definitions, with the treatment effect stable at around 15% with full fixed effects. In the full sample without restrictions, the effect size decreases to 4% without fixed effects, likely due to increased noise from irrelevant connections. However, the effect rises to 10.5% when including fixed effects, demonstrating robustness even in the most inclusive scenario.

This consistency across different relavance definitions strengthens my main findings, suggesting that the observed knowledge transfer effect is not an artifact of sample construction but a genuine phenomenon in worker mobility.

6.3 Quantification of Effects

(to be developed)

7 Conclusion

This study provides novel insights into the critical role of worker mobility in shaping firm networks and competitive dynamics. By leveraging a unique dataset combining employer-employee matched data with comprehensive firm-to-firm transaction records, I quantify the significant impact of worker transitions on a recruiting firm's ability to acquire new customers. My findings reveal that customer-specific knowledge transferred through worker mobility increases the likelihood of new business connections by 15% on average.

The research highlights several key aspects of this knowledge transfer process. The effect is more pronounced for contact workers in customer-facing roles, compared to routine workers, underscoring the importance of relationship-specific knowledge. Younger and smaller recruiting firms benefit more from this knowledge transfer, suggesting its particular value for firms with limited experience and resources. Workers transferring valuable network knowledge experience substantial wage premiums, and the origin firms face increased customer attrition due to competition from recruiting firms.

These findings have important implications for strategic human capital management and labor policies. They suggest that firms can leverage strategic hiring to expand their customer base and enhance their competitive position. For policymakers, this research provides empirical evidence on the effects of labor mobility restrictions, such as non-compete agreements, on knowledge diffusion and market dynamics.

Future research could explore the long-term effects of this knowledge transfer on firm performance, investigate industry-specific variations, and examine how firms can best retain valuable network knowledge. Additionally, studies could explore the balance between fostering innovation through labor mobility and protecting proprietary information.

In conclusion, this study reveals the complex relationship between worker movement and business networks, showing how the flow of workers shapes relationships between companies and competitive landscapes. It emphasizes the strategic importance of employees not just for their direct work output, but also for their role in creating valuable network connections.

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A Data Construction

I aim to produce a dataset that explores buyer-seller variation on the knowledge of workers. I begin with approximately 50 million worker movements extracted from employer-employee matched data, which covers all labor mobility events in the economy. Between 2012 and 2020, there are around 5.5 million movement events involving 3.5 million contact workers,

I apply several filters to refine the dataset. First, I restrict the sample to workers employed for at least one year at their origin firms, reducing the number of movements to 2.5 million. To minimize the impact of pre-existing relationships between firms, I exclude cases where more than 10 coworkers move together in a given year.

Next, I create a list of newly acquired customers for the origin firms within a one-year window before and after the recruitment event. To ensure a fair comparison, I exclude customers acquired by the origin firm two or more years before the recruitment.

I then identify potentially relevant customers for the recruiting firm, defined as those that have made purchases from at least one firm in the same 4-digit industry as the recruiting firm during the first sample year. This dimension reduction tool decreases the pool of customers by 90%, but the remaining firms account for more than 66% of purchases from recruiting firms. Additionally, I require that the recruiting firm has not sold to that customer before the recruitment.

To avoid inflating the dataset, I exclude movements from "super-connected" firms, defined as those that acquire over 100 new potentially relevant customers annually, typically distributors, wholesalers, or retail chains. This removes 50,000 movements generated by 3,500 firms.

After applying these filters, I focus on approximately 1 million movements from origin firms with at least one potentially relevant customer for the recruiting firm. For robustness checks, I relax the restriction to potentially relevant firms in the advertisement industry to assess the sensitivity of my results to this criterion.

I further refine the dataset by excluding customers that did not survive in both the year before and after the recruitment event and origin firms that acquired a potentially relevant customer only once during this period. This helps isolate the impact of worker knowledge transfer from other factors affecting the origin firm's network outcomes.

For recruiting-firm customer pairs appearing more than once, I use the earliest movement instance. If multiple movements occur simultaneously, I randomly select one.

Finally, I merge this refined list with VAT data and check each year whether the recruiting firm sold to the identified customers around the recruitment period. By construction, the link formation dummy is always zero before recruitment and can be zero or one in subsequent years.

A.1 Descriptive Statistics of Firms, Workers, and Networks

Tables 11, 12, 13, and 14 provide an overview of the key characteristics of origin firms, recruiting firms, workers, and worker knowledge in my sample.

Table 11 shows that origin firms in the final sample are generally larger and more productive than the average firm involved in worker movements, with higher mean values for number of workers, sales, and network connections.

Table 12 indicates that recruiting firms in the final sample are also larger than the average firm involved in worker movements, but the difference is less pronounced than for origin firms.

Worker characteristics are presented in Table 13. Workers in the final sample have higher daily wages and longer tenures at both recruiting and origin firms compared to all contact workers.

Table 14 focuses on worker knowledge and wage growth. On average, workers in my sample are associated with 29.5 "relevant potential customers" and 261.5 total customers from their origin firms. The mean change in log real wage for workers moving between firms is 0.06, indicating a positive wage growth on average.

These statistics provide context for interpreting the subsequent analyses of knowledge transfer through worker mobility and its impact on firm networks and worker wages.

Table 11: Summary Statistics for Origin Firms

	Final Sample			All Movements		
	Mean	SD	Median	Mean	SD	Median
#Workers	75.15	408.51	9.00	17.65	17.50	11.00
Export Status	0.33	0.47	0.00	0.16	0.37	0.00
Sales (Real)	31,000.84	493,100.50	4,335.75	4,428.30	111,400.90	451.07
Labor Productivity	4.03	3.13	4.00	3.99	1.27	1.83
# Sellers	57.56	114.83	31.00	14.57	43.37	5.00
# Buyers	69.64	264.19	28.00	12.73	64.30	5.00
Firm Age	15.57	12.75	12.00	17.65	17.50	11.00
N		98,887			1,186,597	

This table presents summary statistics for origin firms in the final sample and for all movements. It shows key characteristics such as number of workers, export status, sales, labor productivity, number of buyers and sellers, and firm age.

Table 12: Summary Statistics for Recruiting Firms

	Final Sample			All Movements		
	Mean	SD	Median	Mean	SD	Median
#Workers	42.31	254.70	8.50	11.91	96.71	3.25
Export Status	0.22	0.42	0.00	0.15	0.36	0.00
Sales (Real)	16,386.99	260,506.30	1,330.27	3,813.42	107,779.30	421.35
Labor Productivity	0.88	1.27	3.86	3.98	1.42	3.83
# Sellers	33.12	80.26	13.00	12.35	32.00	5.00
# Buyers	38.81	150.38	9.00	12.77	59.31	8.00
Firm Age	14.64	15.58	9.00	16.97	18.37	9.00
N		161,067			1,145,435	

This table presents summary statistics for recruiting firms in the final sample and for all movements. It shows key characteristics such as number of workers, export status, sales, labor productivity, number of buyers and sellers, and firm age.

Table 13: Summary Statistics for Workers

Variable	Final Sample Mean	SD	Median	All Contact Workers Mean	SD	Median
Daily Wage(real)	57.45	45.34	42.18	48.02	31.62	40.43
Worker Age	31.99	8.93	31	30.74	9.53	29
Women Dummy	0.28	0.45	1	0.31	0.46	1
Tenure at Recruiting Firm (quarters)	5.38	5.75	3	4.70	5.37	2
Tenure at Origin Firm (quarters)	8.56	5.52	7	3.71	5.19	1
N		663,448			7,037,518	

This table presents summary statistics for workers in the final sample and for all contact workers. It shows key characteristics such as daily wage, age, gender, and tenure at both recruiting and origin firms.

Table 14: Summary Statistics of Worker Knowledge and Wage Growth

	Mean	SD	Median
# Relevant Potential Customers	29.5	47.8	11
# Total Customers	261.5	846.4	85
Δ Log Real Wage	0.05	0.19	0
# Workers		413,835	
Observations		779,225	

Notes: This table presents summary statistics for key variables in the wage regression analysis. Relevant Potential Customers refer to customers of the origin firm that have purchased from at least one firm in the same industry as the recruiting firm. # Total Customers is the total customer base of the origin firm. Δ Log Real Wage is the difference in log real wages between the recruiting firm and the origin firm. The sample includes contact workers who moved between firms during the sample period.

B Event Study

While the cross-sectional analysis provides a snapshot of the network overlap just before recruitment, it does not capture the dynamic evolution of this relationship. The significant cross-sectional difference I observed prompts further investigation into how this overlap changes over time, offering insights into the co-evolution of labor and product networks.

To explore this dynamic aspect, I conduct an event study analysis. I create a buyer-seller level dataset where the seller is the recruiting firm and the buyer is a customer of the origin firm. My coefficient of interest is whether there is a sale by the recruiting firm to a customer from the origin firm's pool, observed at different time points relative to the recruitment event.

This approach allows me to trace the trajectory of network overlap around the worker transition. By doing so, I can better understand how the labor network (represented by worker movement) and the product network (represented by customer relationships) interact and co-evolve over time.

I estimate the following regression:

$$a_{s,b,t} = \sum_{k=-4,k\neq-1}^{k=4} \beta_k \mathbb{1}[t = t_i + k] + seller_s + buyer_b + year_t + \epsilon_{s,b,t} \tag{6}$$

where $a_{s,b,t}$ is a link formation dummy, and the term t_i denotes the year when firm i recruits the contact worker.

Figure 3 plots the resulting beta coefficients, illustrating the trajectory of sale probability around the recruitment event.

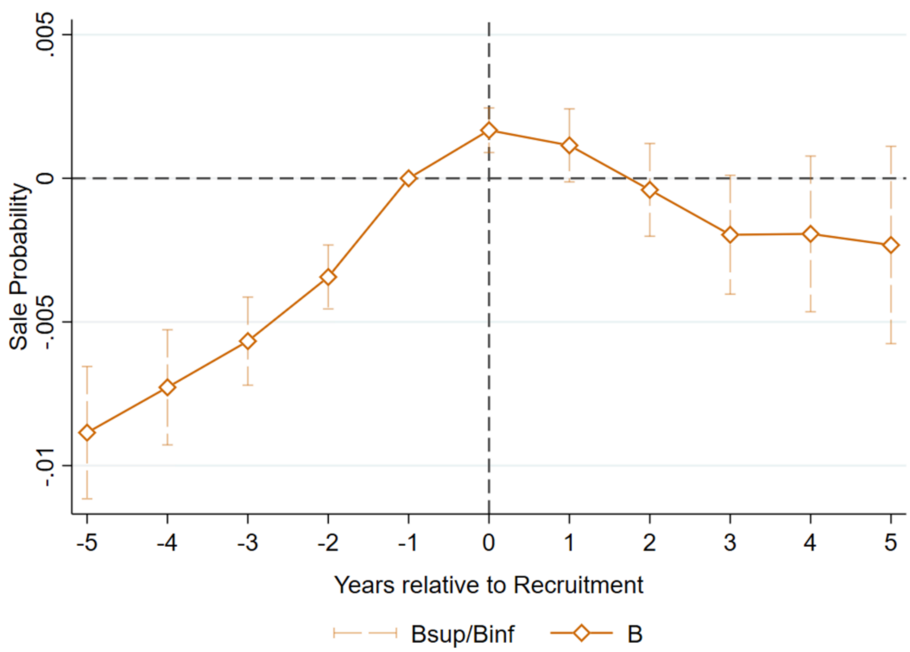


Figure 3: The trajectory of the sale probability to the treatment group around the recruitment of the contact worker, where the period is the year relative to the recruitment of the worker. The graph presents the beta coefficients of a regression of the link formation dummy in the buyer-seller-year level on period dummies.

The results reveal a gradual increase in sale probability leading up to the recruitment event. This suggests that the recruiting firm begins forming relationships with the origin firm's customers even before formally hiring the worker, indicating a pre-existing and evolving network alignment.

Moreover, I observe that the customer overlap tends to plateau around the year of recruitment. This plateau highlights the convergence of networks as the recruitment period approaches, suggesting that the unobserved heterogeneity in network suitability has a dynamic component. The networks of the origin and recruiting firms appear to gradually align over time, independent of the specific worker movement.

These findings underscore the complexity of identifying the causal impact of worker knowledge transfer. The overlapping and co-evolving nature of these networks makes it challenging to disentangle the direct effect of the recruited worker's knowledge from the underlying network dynamics. Consequently, more sophisticated empirical strategies are necessary to address the unobserved heterogeneity arising from the intertwined nature of labor mobility and production networks. Figure 3 demonstrates a significant increase in new customers for the recruiting firm, alongside a noticeable decline in their existing customer base. These patterns suggest that recruiting firms effectively leverage the contact workers' knowledge, shifting their focus from established customers to newly identified ones. This transition underlines the strategic utilization of the worker's network to explore and establish fresh business connections, diverging from the firm's prior customer engagements.

C Robustness and Sensitivity Tests

To ensure the validity and reliability of our main findings, we conduct a series of robustness checks and sensitivity analyses. These tests help to address potential concerns about the empirical strategy and strengthen the credibility of our results.

C.1 Balance Tests

A crucial assumption in our identification strategy is that the treatment and control groups are comparable in terms of observable characteristics. To verify this, we conduct balance tests on key firm attributes for both contact workers and routine workers.

	(1) Sales (log real)	(2) Employment(log)	(3) Firm Age	(4) #Customers	(5) # Suppliers
Treatment	-0.041***	-0.047***	-0.100***	-0.055***	-0.020***
	(0.007)	(0.005)	(0.019)	(0.006)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes
Movement FE	Yes	Yes	Yes	Yes	Yes
Observations	8,247,895	8,247,895	8,247,895	8,247,895 8,247,895	
R^2	0.322	0.301	0.126	0.264	0.319

Standard errors are clustered around the 4-digit seller NACE2 code.

Table 15: Balance Test for Contact Workers: The treatment firms are those that are acquired by the origin firm one year before the recruitment while control groups are acquired one year after the recruitment. The sample consists of a cross-section of firms in the year of recruitment.

Table 15 presents the results of the balance test for contact workers. We compare firms in the treatment group (those acquired by the origin firm one year before recruitment) with firms in the control group (those acquired one year after recruitment). The results show that firms in the control group are slightly larger, with approximately 2% more suppliers and 4% more sales on average. While these differences are statistically significant, they are economically small. Importantly, any potential advantage is more likely to favor the control group, which would work against finding a significant effect of worker knowledge on the formation of new buyer-seller links. This suggests that our estimates of the effect of worker knowledge transfer are, if anything, conservative.

For routine workers, we conduct a similar balance test, as shown in Table 16. The patterns observed are consistent with those for contact workers, with control group firms being slightly larger and having more customers and suppliers. Again, these differences are statistically significant but small in magnitude.

The presence of these small differences underscores the importance of our empirical specification, which includes various fixed effects to control for time-invariant characteristics of sellers and buyers, as well as time-variant characteristics such as demand conditions. By including seller-year and buyer-year fixed effects in our most stringent specifications, we account for any potential confounding factors that might arise from these slight imbalances between treatment and control groups.

Overall, while the balance tests reveal some minor differences between treatment and control

	(1)	(2)	(3)	(4)	(5)
	Sales (log real)	Employment(log)	Firm Age	#Customers	# Suppliers
Treatment	-0.037***	-0.044***	-0.046*	-0.060***	-0.025***
	(0.007)	(0.006)	(0.020)	(0.007)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes
Movement FE	Yes	Yes	Yes	Yes	Yes
Observations	6,881,184	6,881,184	6,881,184	6,881,184	6,881,184
R^2	0.322	0.300	0.116	0.267	0.310

Standard errors are clustered around 4-digit seller NACE2 code.

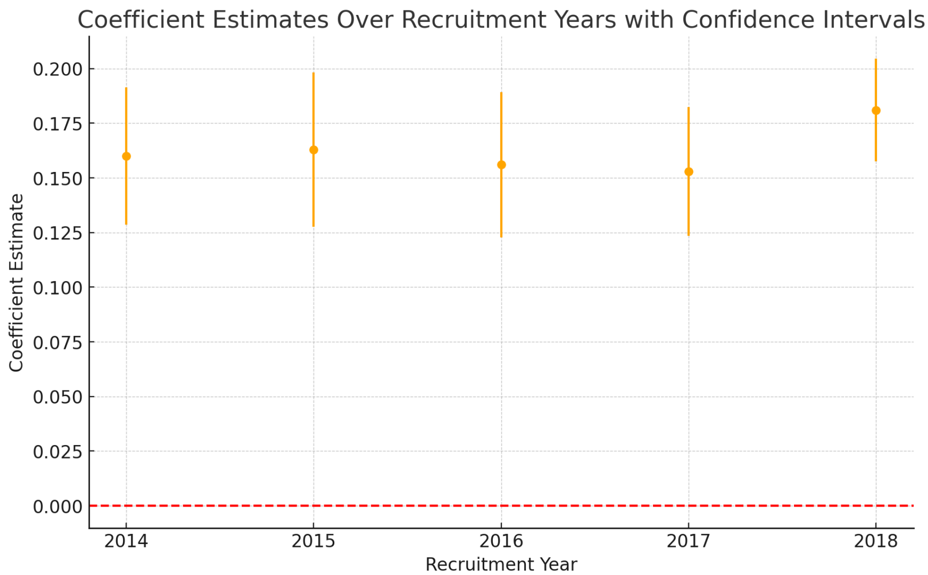
Table 16: Balance Test for Routine Workers: The treatment firms are those that are acquired by the origin firm one year before the recruitment while control groups are acquired one year after the recruitment. The sample consists of a cross-section of firms in the year of recruitment.

groups, these differences are small and, if anything, would lead to underestimation of our main effects. This lends further credibility to our findings on the impact of worker knowledge transfer on network formation and firm outcomes.

C.2 Heterogeneity across Cohorts

To ensure the robustness of results from pooled data of over 300,000 worker movements across five years, I conducted three distinct analyses to address potential heterogeneity across cohorts. First, I estimated the treatment effect separately for each recruitment year cohort using the main analysis regression model. This approach helps identify whether the treatment effect varies significantly across different time periods.

Figure 4: Coefficient Estimates Over Recruitment Years with Confidence Intervals



Notes: This figure shows the impact of worker knowledge transfer on link formation, estimated separately for each recruitment year cohort. The analysis uses the same regression model as in the main analysis, applied across different cohorts to assess whether the treatment effect varies significantly over time. The coefficients represent the change in the probability of forming new business connections due to knowledge transfer facilitated by worker mobility.

As shown in Figure 4, the effect of worker knowledge transfer is consistent across cohorts, with no significant fluctuations over the years. This consistency suggests that the pooled analysis does not obscure meaningful differences across time.

Two-Way Fixed Effects (TWFE) Regression

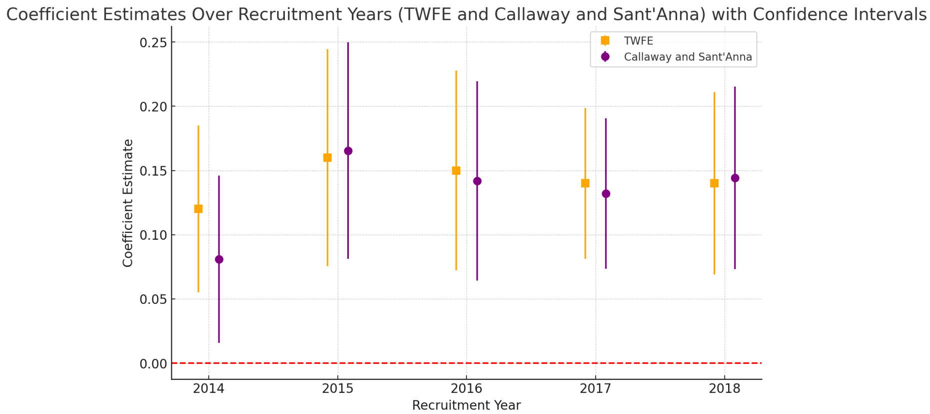
Next, I employed a Two-Way Fixed Effects (TWFE) approach, including pre-period data:

$$a_{s,b,t} = \alpha + \beta_1 \text{Post} + \beta_2 \left(\text{Post} \times \mathbb{1}\left[(\text{s,b}) \in \text{K. Treatment}\right]\right) + \gamma_s + \delta_b + \eta_t + \nu_{s,b,t} \tag{7}$$

This formulation yields similar results to the main analysis by comparing post-recruitment groups, as the treatment and control groups have the same pre-recruitment value of 0 by construction, given that the recruiting firm has no sales to these groups before recruitment.

To account for potential bias in TWFE models when treatment effects vary across time, I applied the Callaway and Sant'Anna (2021) method. This approach mitigates bias due to treatment effect heterogeneity by creating clean control groups, using only not-yet-treated units as controls for

Figure 5: Coefficient Estimates Over Recruitment Years (TWFE and Callaway and Sant'Anna) with Confidence Intervals



Notes: This figure compares the impact of worker knowledge transfer on link formation across recruitment years using Two-Way Fixed Effects (TWFE) and the Callaway and Sant'Anna (CS) approach. The TWFE method, shown in orange, controls for firm-level and time-specific effects. The CS method, shown in purple, accounts for variation in treatment timing and heterogeneity in treatment effects across cohorts by estimating and then aggregating group-specific treatment effects.

treated units at each point in time. It also avoids the negative weighting problem associated with TWFE models, where some treatment effects can receive negative weights when averaging across groups and time period.

Figure 5 compares results from the TWFE and Callaway-Sant'Anna methods. The consistency across these approaches strengthens the validity of the main results. Both methods yield similar estimates across the recruitment years, confirming that the findings are not biased by cohort heterogeneity. The robustness of these results across different methodological approaches and cohorts reinforces the central finding that worker knowledge transfer significantly increases the likelihood of forming new business connections. This consistency suggests that the effect is not driven by particular time periods or methodological artifacts, but represents a stable phenomenon in the data.

C.3 Robustness: Varying Control Group Thresholds

To further validate the robustness of my main findings, I examine the sensitivity of the results to different thresholds for defining the control group. While maintaining the knowledge treatment group as customers acquired by the origin firm exactly one year before the worker's transition, I vary the cutoff for the control group from one to four years post-transition. The treatment group remains unchanged due to the relatively short average tenure of workers at the origin firm, which limits their exposure to customers acquired later in their tenure. This approach allows me to assess the stability of the observed knowledge transfer effect and explore potential temporal dynamics in the formation of new business connections.

Figure 6 presents the coefficient estimates for the knowledge treatment effect under these varying control group definitions. The baseline result from my main analysis, which uses a one-year post-transition cutoff for the control group, shows a coefficient of 0.146. As I extend the control group threshold further into the future, I observe a gradual increase in the magnitude of the coefficient, reaching 0.30 for a four-year cutoff.

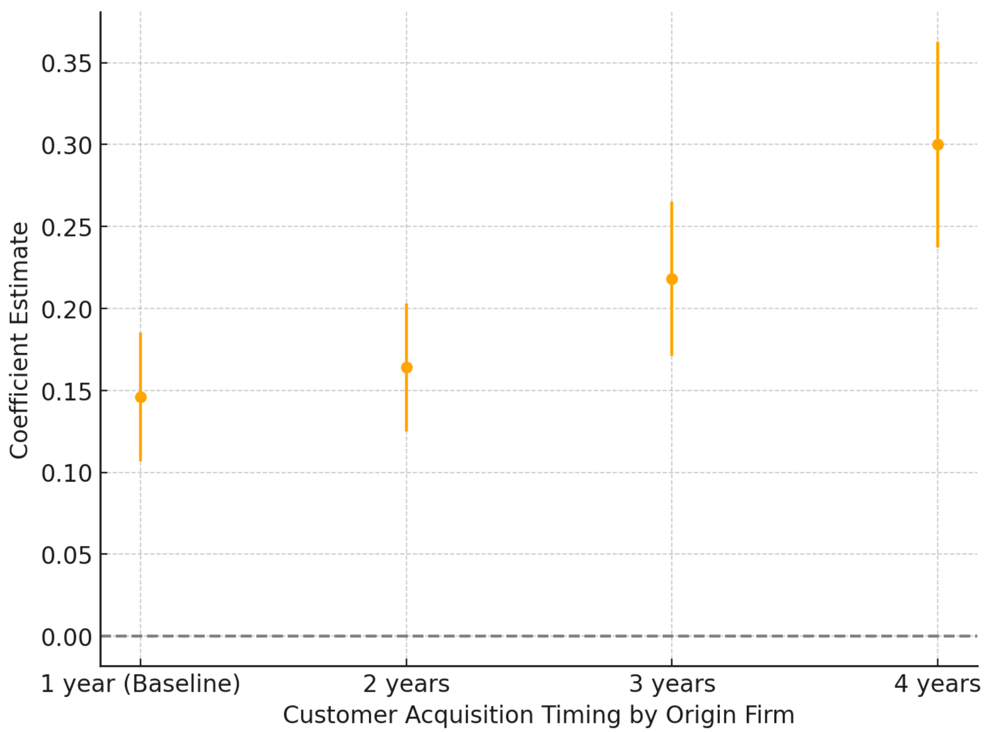


Figure 6: Coefficient estimates for knowledge treatment effect under varying control group thresholds

Several factors may contribute to this observed pattern. As the time gap between the acquisition of treatment and control group customers widens, the likelihood of information leakage to the transitioning worker about control group customers diminishes. This decreasing probability of exposure to information about newer customers aligns with the intuition that workers are less likely to gain knowledge about customers acquired long after their departure.

Crucially, the coefficients for one-year and two-year cutoffs are statistically indistinguishable, suggesting that my main results are robust to small variations in the control group definition. This stability reinforces the validity of my primary empirical strategy and strengthens confidence in the identified knowledge transfer effect.

The increasing trend in coefficients for longer cutoffs, however, warrants cautious interpretation. While it may reflect a genuine intensification of the knowledge transfer effect due to reduced information leakage, it could also capture other time-varying factors unrelated to worker knowledge. As the temporal distance between treatment and control groups expands, the potential for confounding influences—such as broader market trends or firm-specific developments—also grows.

It's worth noting that some attempts to acquire customers may have begun earlier than their official acquisition date, and workers might learn about potential future customers from past coworkers. However, these effects are likely to diminish over time, contributing to the observed pattern in the coefficients.

In sum, this robustness check demonstrates the stability of my main findings for nearby control group thresholds and reveals intriguing temporal dynamics in network formation. The results underscore the importance of my empirical strategy in isolating the immediate effects of worker knowledge transfer while highlighting the complexities of long-term network evolution. The increasing coefficients for longer time gaps suggest that the knowledge advantage of recruited workers becomes more pronounced when compared to customers acquired much later by the origin firm, though this interpretation should be tempered by the potential for increased confounding factors over longer time horizons.

C.4 Robustness Check: All Worker Movements

To ensure the robustness of our main findings, we extend our analysis to include all 1.2 million worker movements in our dataset, rather than just the refined sample used in our primary analysis.

This broader sample allows us to verify whether our results hold across a more comprehensive set of worker transitions.

Table 17: Summary Statistics of Worker Movements

	All Contact Workers			Final Sample		
Variable	**Median**	**Mean**	**SD**	**Median**	**Mean**	**SD**
Movement from Same Industry	0	-0.33	0.47	0	0.37	0.48
Movement from Same Province	1	0.67	0.47	1	0.63	0.48
Recruiting Firm Employees	41.5	1336	5251	57.5	652	3075
Origin Firm Employees	47.25	1730	3464.641	196	1456	4150
Recruiting Firm Buyers	23	227	957	37	223	961
Origin Firm Buyers	24	212	968	86	282.2	958
Relevant Potential Customers	0	4.61	11.9	5	10	12
# Movements		1,219,178			297,359	

Notes: This table presents summary statistics for worker movements for all movements.

Table 17 presents summary statistics comparing all contact worker movements to our final sample, highlighting key differences in firm characteristics and relevance. Notable differences include a higher rate of same-industry movements in the final sample, larger average firm sizes, and significantly more“relevant potential customer” in the final sample compared to all movements.

Table 18 presents a comparison between our main results using the network control approach for contact workers and the results for all worker movements without sample restrictions.

Table 18: The Effect of Knowledge: Network Control vs. All Worker Movements

	Baseline Sample		All Worker Movements	
	(1) Link Formation	(2) Link Formation	(3) Link Formation	(4) Link Formation
Knowledge Treatment	0.146***	0.150***	0.110***	0.134***
	(0.005)	(0.021)	(0.003)	(0.031)
Year FEs		Yes		Yes
Seller FEs		Yes		Yes
Buyer FEs		Yes		Yes
BuyerYear FEs		Yes		Yes
SellerYear FEs		Yes		Yes
Observations	16,348,242	16,348,242	90,702,617	90,702,617
R^2	0.000	0.209	0.000	0.129

Notes: This table compares the estimated effect of worker knowledge transfer on the probability of forming new business connections. The left panel shows results using the network control approach for contact workers from our main analysis. The right panel presents the baseline results without sample restrictions, including all 1.2 million worker movements. In both cases, the treatment group consists of customers acquired by the origin firm during the worker's tenure. The data is at the buyer-seller-year level, with the selling firm being the recruiting firm, and includes only post-recruitment years. Values are normalized using the mean link formation dummy. Standard errors are clustered around 4-digit NACE2 code.

As shown in Table 18, the positive effect of worker knowledge transfer on link formation persists even when considering all worker movements. In the baseline specification without controls (column 3), we observe an 11% increase in the probability of forming a new connection with a customer in the Knowledge Treatment Group compared to the Control Group. This effect strengthens to 13.4% when including our most comprehensive set of fixed effects (column 4).

These findings are consistent with our main results for contact workers, albeit with slightly lower magnitudes. In our primary analysis using the network control approach (columns 1 and 2), we found a 14.6% increase in link formation probability without controls, rising to 15% with full controls.

The persistence of a significant positive effect across this broader sample reinforces the robustness of our primary conclusions. Despite the inclusion of movements that may involve less customer-specific knowledge transfer, we still observe a substantial impact on network formation.

The differences in effect sizes between the contact worker sample and the full sample can be attributed to several factors:

The differences in effect sizes between the contact worker sample and the full sample can be attributed to two main factors. First, there is a dilution effect: The inclusion of all worker movements likely incorporates transitions where customer-specific knowledge is less relevant or transferable, potentially diluting the overall effect. Second, the sample composition plays a role: As indicated in Table 17, the full sample includes a wider range of firm sizes and network characteristics, which may influence the magnitude of knowledge transfer effects.

Despite these differences, the consistent positive and significant effect across both samples provides strong evidence for the robustness of our findings. It suggests that the phenomenon of customer-specific knowledge transfer through worker mobility is not limited to our carefully selected sample of contact workers but is a widespread occurrence across various types of worker movements.

This robustness check strengthens our main conclusions about the importance of worker mobility in shaping firm networks and competitive dynamics, demonstrating that the effects persist even when considering a broader, less restrictive sample of worker movements.

C.5 Temporal Dynamics of Knowledge Transfer Effects

To gain a deeper understanding of how the impact of knowledge transfer evolves over time, we examine the temporal dynamics of the effect following worker recruitment. Figure 7 illustrates the evolution of the knowledge transfer effect on the recruiting firm's ability to establish new customer connections in the years following a worker's transition.

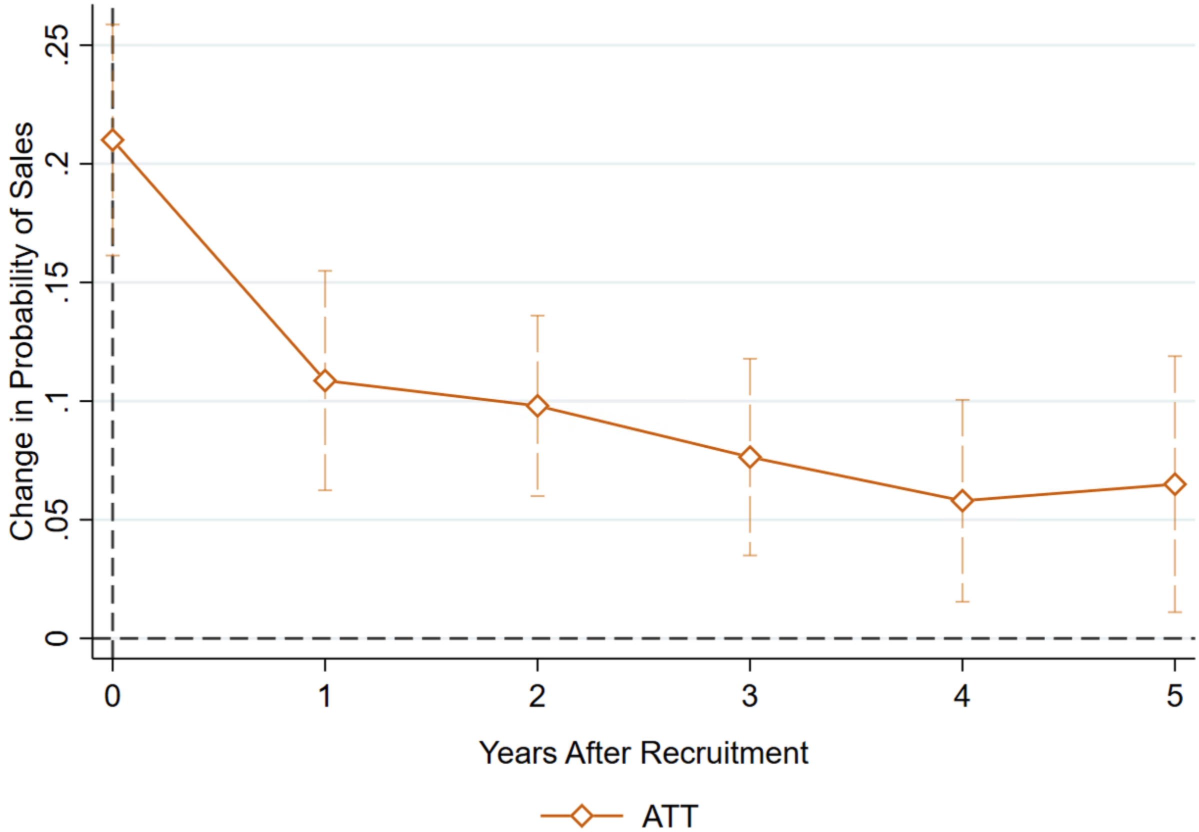


Figure 7: Temporal evolution of worker knowledge transfer effects on new customer connections. The x-axis represents the number of years after the worker transition event, with period 0 being the year when the worker joined the recruiting firm. The y-axis shows the magnitude of the effect on the probability of forming new connections.

The results reveal a clear temporal pattern in the knowledge transfer effect. The impact is most pronounced in the year of recruitment (period 0), indicating an immediate boost to the recruiting firm's network formation capabilities. This strong initial effect aligns with the idea that newly acquired customer-specific knowledge is most valuable and actionable upon the worker's arrival.

Interestingly, the effect persists in the subsequent years but exhibits a gradual decline. There is a substantial decrease in magnitude after the third year post-recruitment. This pattern is consistent with the average tenure of workers in our sample, which is approximately 5.5 quarters (about 1.4 years) in the recruiting firm. The stronger effect observed in the initial years likely reflects the period when the transferred knowledge is most current and relevant.

The observed temporal dynamics suggest that while the benefits of knowledge transfer through worker mobility are significant and immediate, they may be subject to depreciation over time. This could be due to various factors, such as the gradual outdating of customer-specific information, the diffusion of knowledge within the recruiting firm, or changes in market conditions that affect the relevance of the transferred knowledge.

These findings have important implications for understanding the long-term value of strategic hiring and the optimal timing for leveraging acquired customer-specific knowledge in expanding firm networks.

C.6 Sensitivity Analysis for Threshold of Determining Treatment and Control Groups

(to be developed)

C.7 Industry Heterogeneity

Our analysis reveals significant heterogeneity in the impact of worker knowledge transfer across different industries. The strongest effects are observed in a diverse range of sectors, providing nuanced insights into the value of connection knowledge in various business contexts.

Service sectors, such as human health activities, travel agencies, and computer programming, demonstrate some of the highest effects. This aligns with the understanding that in service-oriented businesses, personal relationships and specific client knowledge are crucial. The transfer of customer-specific information through worker mobility in these industries appears particularly valuable, likely due to the highly personalized nature of services and the importance of trust and familiarity in client relationships.

Notably, several manufacturing sectors traditionally considered as lower value-added, including furniture, textiles, and paper products, also exhibit strong effects. This finding highlights that in these industries, connection knowledge brought by new recruits plays a significant role in expanding customer networks. While these sectors may involve some standardized processes, they often require understanding specific customer needs, production capabilities, or niche market opportunities, making insider knowledge valuable.

The wholesale trade sector shows above-average effects, as expected. This underscores the importance of relationship-specific knowledge and personal connections in B2B transactions within the distribution chain. The strong effect in wholesale trade suggests that knowledge of supplier networks, purchasing patterns, and specific business needs of other firms is highly valuable when transferred through worker mobility.

In contrast, industries such as chemicals manufacturing, land transport, and postal activities show relatively weaker effects. This could indicate that in these sectors, customer relationships are more standardized or that other factors, such as pricing or logistical efficiency, play a more dominant role in customer acquisition and retention than personal connections or insider knowledge.

The manufacturing sector overall shows a mixed picture. While some segments show strong effects, others, like machinery and equipment or motor vehicle manufacturing, display more moderate impacts. This variability likely reflects differences in the complexity of products, the nature of buyer-seller relationships, or the degree of customization required in different manufacturing subsectors.

The construction industry shows moderate effects, possibly reflecting a balance between the importance of personal connections in securing contracts and the role of more standardized bidding processes in many construction projects.

This heterogeneous pattern across industries underscores the complex nature of customer relationships and the varied importance of tacit knowledge in different business contexts. It suggests that the value of connection knowledge transferred through worker mobility is not uniformly high or low across the economy, but rather highly dependent on the specific characteristics of each industry. These findings have important implications for understanding the strategic value of hiring decisions and the potential competitive advantages that can be gained through the strategic acquisition of workers with valuable customer knowledge.

Table 19: Industry-Level Heterogeneity of Treatment Effect

Industry	Coefficient	SD
Manufacture of food products	0.166***	(0.041)
Manufacture of textiles	0.209***	(0.048)
Manufacture of wearing apparel	0.163***	(0.048)
Manufacture of paper and paper products	0.203*	(0.122)
Manufacture of chemicals and chemical products	0.012	(0.103)
Manufacture of rubber and plastic products	0.162*	(0.087)
Manufacture of other non-metallic mineral products	0.160	(0.119)
Manufacture of fabricated metal products, excep...	0.150	(0.104)
Manufacture of electrical equipment	0.155	(0.110)
Manufacture of machinery and equipment n.e.c.	0.063	(0.101)
Manufacture of motor vehicles, trailers and sem...	0.104	(0.134)
Manufacture of furniture	0.201***	(0.069)
Construction of buildings	0.181***	(0.065)
Specialised construction activities	0.091	(0.120)
Wholesale and retail trade and repair of motor ...	0.168***	(0.031)
Wholesale trade, except of motor vehicles and m...	0.187***	(0.010)
Retail trade, except of motor vehicles and moto...	0.174***	(0.019)
Land transport and transport via pipelines	0.005	(0.072)
Warehousing and support activities for transpor...	0.179**	(0.083)
Postal and courier activities	0.025	(0.113)
Accommodation	0.099***	(0.027)
Food and beverage service activities	0.152***	(0.043)
Computer programming, consultancy and related a...	0.170**	(0.074)
Real estate activities	0.063	(0.156)
Activities of head offices; management consulta...	0.172	(0.127)
Architectural and engineering activities; techn...	0.133	(0.102)
Advertising and market research	0.136*	(0.072)
Travel agency, tour operator and other reservat...	0.234***	(0.061)
Security and investigation activities	-0.183	(0.194)
Services to buildings and landscape activities	0.136	(0.172)
Office administrative, office support and other...	-0.077	(0.091)
Human health activities	0.303***	(0.080)

Notes: This table presents estimates of the treatment effect of worker knowledge transfer on the probability of forming new business connections across different industries. The sample includes only contact workers who move between firms. The dependent variable is a dummy for whether the recruiting firm forms a link with a customer from the knowledge treatment group versus the control group. The knowledge treatment group consists of customers acquired by the origin firm during the worker's tenure, while the control group consists of customers acquired by the origin firm after the worker's departure. All specifications include year, seller, and buyer fixed effects. Values are normalized using the mean link formation probability, representing the increase in probability relative to the average probability of link formation. Standard errors (in parentheses) are clustered at the seller-year level. Significance levels: * p ¡ 0.1, ** p ¡ 0.05, *** p ¡ 0.01. The data is at the buyer-seller-year level and includes only post-recruitment years. Industries are classified according to NACE Rev. 2 codes. Coefficients represent the differential effect of worker knowledge on link formation probability for each industry relative to the overall average effect. Due to power issues, industries with fewer than 100,000 observations are not included in this table.

D Theory

In this section, I propose a general equilibrium model of production networks, building on the works of Lim (2018) and Huneeus (2018). My focus is on the role of information transmission by sales managers in endogenous network formation. This model elucidates the mechanisms and explores the welfare implications of information transmission in production networks.

The novel aspect of this model is the incorporation of sales managers as key agents in network formation and maintenance. Sales managers possess specific knowledge about market conditions, customer preferences, and potential new connections, accumulated through their professional experiences. They influence the cost of forming links between firms, with their movement between firms transmitting 'know-who' knowledge, enabling firms to establish connections with new customers or suppliers previously unknown or inaccessible.

Our model consists of a representative household and a continuum of distinct firms, each producing a unique product within a monopolistically competitive market. Firms are heterogeneous in productivity (ϕ) and demand (δ), encapsulated within the variable $\chi = (\phi, \delta)$. The distribution of this heterogeneity across firms is described by a cumulative distribution function G_χ and a corresponding density function g_χ.

Production involves the utilization of labor and inputs from other firms. Inter-firm relationships are governed by relational frictions, with the probability of a firm of type χ acquiring inputs from a type χ' firm given by $m(\chi, \chi')$. Initially, the model assumes no heterogeneity in demand across firms, setting $\delta = 1$.

D.1 Static Model

D.1.1 Households

The household utility function is given by:

$$U = \left[\int_{S_\chi} [x_H(\chi)]^{\frac{\sigma-1}{\sigma}} dG_\chi(\chi) \right]^{\frac{\sigma}{\sigma-1}} \tag{8}$$

I define the household demand shifter:

$$\Delta_H = UP_H^\sigma \tag{9}$$

The household demand is:

$$x_H(\chi) = \Delta_H p_H(\chi)^{-\sigma} \tag{10}$$

where

$$P_H = \left[\int_{S_\chi} (p_H(\chi))^{1-\sigma} dG_\chi(\chi)\right]^{\sigma-1} \tag{11}$$

D.1.2 Firm Production

The production function for each firm is:

$$X(\chi) = \left[[\phi l(\chi)]^{\frac{\sigma-1}{\sigma}} + \int_{S_\chi} m(\chi,\chi')[\alpha x(\chi,\chi')]^{\frac{\sigma-1}{\sigma}} dG_\chi(\chi')\right]^{\frac{\sigma}{\sigma-1}} \tag{12}$$

Given prices $\{p(\chi,\chi')\}_{\chi' \in S_\chi}$, the marginal cost of each χ firm is:

$$\eta(\chi) = \left[\phi^{\sigma-1} + \alpha^{\sigma-1}\int_{S_\chi} m(\chi,\chi')\,[p(\chi,\chi')]^{1-\sigma}\, dG_\chi(\chi')\right]^{\frac{1}{1-\sigma}} \tag{13}$$

The quantities of labor and intermediate inputs demanded are:

$$l(\chi) = X(\chi)\eta(\chi)^\sigma \phi^{\sigma-1} \tag{14}$$

$$x(\chi,\chi') = X(\chi)\eta(\chi)^\sigma \alpha^{\sigma-1} p(\chi,\chi')^{-\sigma} \tag{15}$$

D.1.3 Market Structure

In a monopolistically competitive market, the profit-maximizing price is a standard CES markup over marginal cost:

$$p_H(\chi) = \mu\eta(\chi) \tag{16}$$

$$p(\chi, \chi') = \mu\eta(\chi') \tag{17}$$

where $\mu = \frac{\sigma}{\sigma-1}$.

D.1.4 Market Clearing

Market clearing for labor requires:

$$\int_{\mathcal{S}_\chi} l(\chi) dG_\chi(\chi) = L - L_f \tag{18}$$

Market clearing for the output of a χ firm is:

$$X(\chi) = x_H(\chi) + \int_{\mathcal{S}_\chi} m(\chi', \chi) x(\chi', \chi) dG_\chi(\chi') \tag{19}$$

D.1.5 Static Market Equilibrium

Following Lim (2018), two crucial variables are introduced to resolve the static market within the context of the given matching function $m(\chi, \chi')$:

$$\Phi(\chi) = \eta(\chi)^{1-\sigma} \tag{20}$$

$$\Delta(\chi) = \frac{X(\chi)\eta(\chi)^\sigma}{\Delta_H} \tag{21}$$

These variables represent network-enhanced productivity and demand parameters. The term $\Phi(\chi)$ symbolizes the inverse of the marginal cost function, encapsulating network-influenced productivity. Meanwhile, $\Delta(\chi)$ quantifies the intermediate demand for the firm χ in relation to the household demand shifter Δ_H.

The differential equations defining the network characteristics of firms are:

$$\Phi(\chi) = \left[\phi^{\sigma-1} + \alpha^{\sigma-1}\mu^{1-\sigma} \int_{S_\chi} m(\chi, \chi')\Phi(\chi') dG_\chi(\chi')\right] \tag{22}$$

$$\Delta(\chi) = \mu^{-\sigma} + \mu^{-\sigma}\alpha^{\sigma-1}\int_{S_\chi} m(\chi', \chi)\Delta(\chi')dG_\chi(\chi') \tag{23}$$

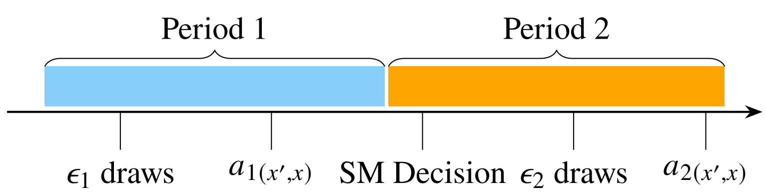
Once I understand a firm's network characteristics through $\Phi(\chi)$ and $\Delta(\chi)$, I can calculate its total revenue, profit, and employment relative to a scaling factor Δ_H.

D.2 Information Flow and Endogenous Network Formation

I now explore how the movements of sales managers and ensuing information flows influence the formation of networks. Each seller faces a fixed cost to establish a new link, denoted as ϵ, which varies randomly across relationships and follows a cumulative distribution function G_ϵ.

Our analysis is structured over two distinct periods. In the initial period, the distribution of information is assumed to be uniform, thereby not impacting the matching function. During this period, sales managers accumulate knowledge about the connections of their employers. This knowledge becomes instrumental in the second period, enabling their new employers to reduce fixed costs for establishing connections within the sales manager's existing network.

To understand the influence of information flow between firms, I introduce $\mathcal{I}(\chi, \chi')$, a function that reflects the degree of knowledge firm χ' has about firm χ. Essentially, $\mathcal{I}(\chi, \chi')$ measures how well-informed one firm is about the other, reducing fixed costs in the network formation process.



An activation matrix is defined for each period, indicating whether firm χ finds it profitable to sell to firm χ' after accounting for information flows. In the second period, the activation matrix is as follows:

$$\underbrace{a_{2(\chi',\chi)}}_{\text{Activation Matrix}} = \mathbb{1}[\underbrace{\pi_{\chi',\chi}}_{\text{Profit}} > \underbrace{\epsilon_{\chi',\chi}}_{\text{Fixed Cost}} - \nu \underbrace{\mathcal{I}^f_{\chi',\chi}(a_1, s)}_{\text{Information}}] \tag{24}$$

For the first-period activation matrix, the difference is that firms take the option value into account and there is no effect of information.

The value functions

$$V_{\chi,2}(a_1, SM_1) = \underset{a_2, SM_2}{\arg\max} \sum_{\chi'} a_{2(\chi',\chi)} \left[\pi_{\chi',\chi} - \epsilon_{\chi',\chi} + \nu \mathcal{I}(\chi', \chi, SM_2)\right] \tag{25}$$

$$V_{\chi,1} = \underset{a_1}{\arg\max} \left\{ \sum_{\chi'} a_{1(\chi',\chi)} \left[\pi_{\chi',\chi} - \epsilon_{\chi',\chi}\right] + \beta V_{\chi,2}(a_1, SM_1) \right\} \tag{26}$$

$SM_t(\chi)$ represents the sales manager of firm χ at time t. $\mathcal{I}^s_{\chi'}(a_1)$ denotes the information function of this sales manager. Note that, managers accumulate knowledge about customers in the first period, which they use in the second period.

$$\mathcal{I}^s_{\chi'}(a_1) = \begin{cases} 1 & \text{if } s = SM_1(\chi) \quad \& \quad a_{1(\chi',\chi)} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{27}$$

In words, the sales manager knows about the firms that were customers of the firm of their employer at period 1. With that I can define the information of the firm depending on the sales manager's movements and previous transactions as follows:

$$\mathcal{I}^f_{\chi',\chi}(a_1, s) = \begin{cases} 1 & \text{if} \quad a_{1(\chi',\chi)} = 1 \quad \& \quad \mathcal{I}^s_{\chi'}(a_1) = 1 \\ 1-\kappa & \text{if} \quad a_{1(\chi',\chi)} = 1 \quad \& \quad \mathcal{I}^s_{\chi'}(a_1) = 0 \\ \theta & \text{if} \quad a_{1(\chi',\chi)} = 0 \quad \& \quad \mathcal{I}^s_{\chi'}(a_1) = 1 \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

where κ is the portion of the information that was embodied in sales managers lost by the origin firm when the sales manager moves out of the firm while $\theta < 1$ measures the degree of knowledge transfer.

In words, firms retain customer information upon a sale. However, if the sales manager responsible for acquiring that customer departs, the quality of this retained information deteriorates, with the knowledge degrading to a factor of $1-\kappa$ unless the new sales manager also knows about that customer. Conversely, firms can gain insights into new customers through newly hired sales managers, although the quality of this information, denoted by $\theta \leq 1$, tends to be lower compared to the case where the firm retained its sales manager from the previous period.

In my model, each firm employs one sales manager. As I progress into the second period, firms decide whether to retain their existing sales managers or to seek new ones. The mobility of sales managers is determined through Nash in Nash bargaining, representing a more strategic and optimized decision-making process than random selection.

The sequence of events unfolds as follows: In the first period, all firms have a sales manager with no experience, and their potential benefits are realized only in period two. In the first period, fixed costs are realized and then the firm assesses the fixed costs associated with each customer match, weighing these against the fixed profits ϵ_1 and the future potential value of customer relationships. Before the second period, firms decide whether to hire a sales manager and which sales manager they will hire, which is settled by Nash in Nash bargaining. Then, fixed costs are realized, and firms decide whether they want to reach each customer by evaluating the profit, fixed cost, and information.

D.3 Choice of Sales Manager

The match probability between two firms x' and x in period t is defined as:

$$m_{x',x}(a_1, s) = \mathbb{P}\left[a_{x',x} = 1\right] = G_\epsilon[\pi_{x',x} + \mathcal{I}^f_{x',x}(a_1, s)] \tag{29}$$

where G_ϵ is the cumulative distribution function of the fixed cost, and $I^f_{x'x}(a_1, s)$ represents the information set of the firm that captures the knowledge transfer from the sales manager s and first-period matches.

The expected benefit for firm x from hiring a sales manager s, given the activation matrix a_1

from the first period, is:

$$U_x(s \mid a_1) = \sum_{x'} E(m_{x',x}(a_1, s)\pi_{x',x}) \tag{30}$$

To quantify the benefit of hiring a specific sales manager s, the customer space is separated into four sets based on the prior sales of the recruiting firm x and the origin firm associated with s:

$$C_{ij}(x,s) = \left\{x' \mid a_{x',x} = i \quad \& \quad \mathcal{I}^s_{x'}(a_1) = j\right\} \tag{31}$$

So there are four sets of C_{00}, C_{01}, C_{10}, C_{11} for each recruiting firm and sales manager pair, x, s. The sets $C_{01}(x,s)$ and $C_{11}(x,s)$ represent customers for which there will be information flow to the recruiting firm x when hiring sales manager s.

Define the expected change in the benefit between two different sales managers: $\Delta U_x(s,s') = U_x(s) - U_x(s')$.

Then the expected change in the benefit by hiring sales manager s compared to hiring no one, $\emptyset$, would be:

$$\begin{aligned}\Delta U_x(s,\emptyset) = &\sum_{x' \in C_{01}} \left[G(\pi(.) + \nu\theta) - G(\pi(.))\right] \pi_{x',x} \\ &+ \sum_{x' \in C_{11}} \left[G(\pi(.) + \nu) - G(\pi(.) + \nu(1-\kappa)\right] \pi_{x',x}\end{aligned} \tag{32}$$

For simplicity, assume $\kappa = 0$ to focus on those customers that the firm had no knowledge of before the recruitment of the sales manager. Then

$$\Delta U_x(s_i,\emptyset) = \sum_{x' \in C_{01}} \left[G(\pi(.) + \nu\theta) - G(\pi(.))\right] \pi_{x',x} \tag{33}$$

Lemma: $\Delta U_x(s_i,\emptyset)$ is an increasing function of the number of customers in the set $C_{01}(x,s_i)$, denoted by $|C_{01}(x,s_i)|$, and the average profit of firm x from selling to firms in the set $C_{01}(x,s_i)$, denoted by $\mathbb{E}[\pi_{x'x} \mid x' \in C_{01}(x,s_i)]$.

The Gale-Shapley deferred acceptance algorithm can be used to find a stable matching, where each firm proposes to the sales manager with the highest surplus $\Delta U_x(s_i, \emptyset)$, and sales managers accept the firm with the highest surplus. This process repeats until no firm wants to make further proposals.

Depending on the structure of the profits and elasticity, the matching algorithm can generate different topologies. These intuitions will help guide the selection problem of control groups and the analysis of sales manager decisions in the model.

D.4 Estimation and Identification

Our model incorporates five distinct sets of parameters:

1. **Fundamental Heterogeneity in Productivity**: I estimate parameters m_ϕ and σ_ϕ to capture the distribution of productivity heterogeneity.
2. **Fixed Cost Shock Distribution**: The parameters m_ϵ and σ_ϵ characterize the distribution of the fixed cost shock.
3. **Information Transmission Process**: Parameters θ, κ, and ν are essential for modeling the information transmission process.
4. **Sales Manager Mobility**: Parameters related to sales manager mobility include σ_{SM}, f_{SM}, and γ.
5. **Market Structure**: Parameters related to market structure include α, σ, L.

These parameters — $m_\phi, \sigma_\phi, m_\epsilon, \sigma_\epsilon, \theta, \kappa, \nu, \sigma_{SM}, f_{SM}, \gamma, \alpha, \sigma, L$ — in conjunction with the distributions of productivity, relationship fixed costs, and sales manager movements, establish the equilibrium of the model.

I calibrate several parameters in my model, following the approach outlined by Lim (2018). These parameters include the labor force L, the labor share of the economy α, and the elasticity of substitution σ. For my analysis, the labor share α is assigned a value of 0.65, reflecting the typical labor share in the economy. Consistent with the standard practice in the literature, σ is set at 3. I set L at 1500, for convenience in scaling.

To estimate the rest of the parameters, I target specific empirical moments:

- Distribution of the number of customers and suppliers.
- Distribution of network sales.
- Number of overlapping customers with origin firms.
- Share of firms that change their sales managers.
- Coefficients from regression analyses: the probability of forming a link in the 'before group' and the impact of utilized customer base on wages.

Each moment plays a vital role in identifying different parameters. For instance:

- The distribution of customers, suppliers, and sales aids in calibrating the parameters related to fundamental productivity and relationship fixed costs.
- The number of overlapping customers and the regression coefficient on the probability of forming a link in the 'before group' assist in identifying θ.
- The correlation of links between periods can reveal insights into ν.
- The origin firm regressions to determine κ.
- The proportion of firms changing sales managers informs the estimation of f_{SM}.
- Wage regression outcomes are crucial for identifying the bargaining parameter γ for sales managers.