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ABSTRACT

An establishment can improve its productivity by hiring workers from more productive establishments. Then, how important is worker reallocation for aggregate productivity growth? To study this question, I develop a general equilibrium model where knowledge transmits as workers reallocate from one job to another. The calibrated model suggests that the knowledge diffusion mechanism increases the aggregate productivity growth by 0.14 percentage points and enhances welfare. Additionally, the mechanism significantly amplifies the adverse effect of firing costs on aggregate outcomes.

JEL Classification: D24, E23, E24, J62, O33, O47

Keywords: knowledge diffusion, firm dynamics, worker reallocation, economic growth

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1 Introduction

Empirically we observe considerable idiosyncratic variation in the firms' productivities and in the demand each of them faces[1]. This emphasizes the importance of the reallocation of the input factors and suggests that policies interfering with efficient allocation can have significant aggregate consequences[2]. Recent literature has shown the effects are not limited to the levels but can also impact the growth path (Poschke, 2009; Mukoymama & Osotimehin, 2019). Traditionally, when exploring how worker flows shape aggregate outcomes, we assume workers to be a resource without memory simply being allocated from one business to another. However, it is likely that workers also diffuse knowledge across establishments, as emphasized by recent growth literature and the wide use of non-compete contracts[3].

In this paper, I evaluate the significance of knowledge diffusion through hiring on aggregate productivity growth. To do so, I start by exploring a reduced-form empirical relationship between a measure of potential knowledge spillover and an establishment's productivity. The information concerning the relevant variables comes from Finnish administrative data that contains details about manufacturing establishments and the individuals who work and move between them. I consider several specifications that allow me to understand how the worker reallocation between establishments affects their productivity.

Two central findings support hiring as a channel of knowledge diffusion. First, for an average establishment, hiring from more productive establishments is connected with a 0.42 percent increase in the following period's productivity. Further, the increase in the establishments' productivity appears to be persistent, as it lasts for at least four years after hiring. Both results align with the previous empirical literature (e.g., Stoyanov & Zubanov, 2012), which indicates that the observed connection is not country-specific.

[1]The large dispersion in firm productivities has been pointed out by, e.g., Syverson (2004). Hottman, Redding & Weinstein (2016) show that over half of the firm size variation can be attributed to demand heterogeneity.

[2]For example, Haltiwanger, Scarpetta & Schweiger (2014) find an empirical relationship between a high level of employment protection and a low pace of job reallocation. The connection between employment protection and productivity has been analyzed, for example, by Moscoso Boedo & Mukoyama (2012), Da-Rocha, Tavares & Restuccia (2016), Raurich, Sánchez-Losada & Vilalta-Bufí (2015) and Autor, Kerr & Kugler (2007).

[3]The role of knowledge flows between producers has been emphasized, e.g., by Lucas (2009), Lucas & Moll (2014), and Perla & Tonetti (2014). Shi (2020) points out that about 64% of executives employed in publicly listed firms have signed non-compete contracts.

Overall, at the micro-level, the worker reallocation appears to shape the evolution of establishment productivities. However, these empirical observations are nevertheless reticent about the aggregate consequences of knowledge spillovers.

To explore the aggregate significance of knowledge diffusion through hiring, I extend a random growth version of Hopenhayn & Rogerson's (1993) model in Poschke (2009) with a knowledge diffusion mechanism. A key feature of the mechanism is that worker potentially retains productivity-enhancing knowledge when changing employer. Workers become available for hire as workers exogenously leave establishments or establishments dismiss workers due to idiosyncratic productivity shock or exit decision. Establishments hire the reallocating workers to expand their operation or replace workers that have left. Some of the workers hired can increase an establishment's productivity due to having previously worked for a more productive employer and can therefore pass on the knowledge. From the establishments' perspective, the potential for attaining new knowledge presents an option to increase productivity at the cost of an additional worker. To what extent establishments choose to exercise this option primarily depends on how likely they are to benefit from the reallocating workers' knowledge, i.e., on their relative position in the productivity distribution.

In the model, the aggregate growth depends on but is not solely defined by knowledge diffusion through worker reallocation. The diffusion directly impacts growth by boosting the mean productivity of incumbent establishments. The rest of the productivity improvements stem from the random-growth mechanism, which operates through productivity shocks. The shocks increase the variance of establishment productivities, i.e., improve some establishments' productivity while forcing others under the profitability limit. The increase in the variance and the simultaneous left-truncation of the productivity distribution due to exiting establishments enhance the mean productivity of incumbents. The economy sustains growth as entrants keep track of the incumbents' growing mean productivity, i.e., they imitate the incumbents.

As knowledge diffusion through hiring is not the sole determinant of aggregate productivity growth, the model offers the required flexibility to isolate its growth contribution. I utilize the flexibility and simultaneously target the micro-level spillover estimate and the aggregate growth rate as a part of my internal calibration. As the spillover estimate informs the knowledge diffusion mechanism, the random growth mechanism explains the remaining part of the aggregate growth. Additionally, the internal calibration includes central moments of establishment dynamics, e.g., establishment size, turnover, and entry rate. The model fit is good across all these dimensions, and, most importantly, the model can replicate the targeted reduced-form connection between worker reallocation and establishment productivity growth.

To obtain the main results, I compare the calibrated economy to a hypothetical one without knowledge diffusion through hiring. The comparison reveals that worker diffused knowledge enhances the mean growth of establishments. Hence, the diffusion increases the worker reallocation, which translates into a 0.14 percentage point increase in aggregate productivity growth and a two and a half percent increase in welfare. Additionally, as the knowledge diffusion mechanism treats establishments asymmetrically, it decreases the mean size of establishments, possibly lowering the welfare. However, the net effect of knowledge diffusion on welfare is positive because the growth effect dominates.

As my results show a strong connection between growth and worker reallocation, labor market policies can significantly affect a country's growth rate. As an illustrative example, I explore the role of firing costs. If Finland adopted the U.S.'s notice period system, it would enhance its growth by 0.1 percentage points and increase welfare by 1.5 percent. To further explore how these results depend on worker transmitted knowledge, I explore the effect of moving from the European level of employment protection legislation to the U.S. system. By examining the legislation change in an economy with and without the knowledge diffusion mechanism, I find that the mechanism amplifies the negative effect of firing costs on growth and welfare by a factor of 1.2–3.

Related Literature

Several studies have explored the connection between firing costs and the aggregate productivity's level and growth. The literature originates from Bentolila & Bertola (1990) and Hopenhayn & Rogerson (1993), who find that firing costs significantly reduce productivity. A similar relationship between firing costs and the level of productivity has also been confirmed in different structural and empirical contexts by, for example, Moscoso Boedo & Mukoyama (2012), Da-Rocha, Tavares & Restuccia (2016), Raurich, Sánchez-Losada & Vilalta-Bufí (2015) and Autor, Kerr & Kugler (2007). By studying the effect of firing costs on aggregate productivity growth explicitly, Poschke (2009) finds that a firing tax decreases aggregate growth if it concerns all producers. Mukoyama & Osotimehin (2019) find a similar negative growth effect for labor adjustment cost in their calibration where entrants' innovations mainly drive the aggregate growth. I offer an additional insight into the firing cost discussion by showing that a firing cost reduces the aggregate growth more when knowledge diffusion through hiring is considered.

The literature has considered the knowledge flow between producers as a source of economic growth.[4] In the most basic version of a knowledge flow model, producers meet at the exogenous frequency. When the producers meet, the knowledge flows from more productive producer to the less productive one. The knowledge flow increases the average productivity and generates aggregate growth in the economy. Further knowledge flow models endogenize the meeting rate. For example, Perla & Tonetti (2014) and Lucas & Moll (2014) consider producers' time allocation decisions between producing and searching for new ideas. The search time determines the meeting frequency and, therefore, individual producers' choices affect aggregate growth. Alvarez, Buera & Lucas (2008, 2013), Perla, Tonetti & Waugh (2021), and Buera & Oberfield (2020) have considered knowledge diffusion in the trade context. In their models, when producers trade goods, they also diffuse knowledge. As the trade diffuses knowledge, the positive effects of trade go beyond the standard reallocation efficiency gains. Similarly, I endogenize the meeting frequency as it depends on the establishments' hiring policy and the distribution of productivities. Moreover, I also show that knowledge diffusion amplifies gains from increasing the reallocation rate by lowering the firing costs.

Literature that originates from the seminal contribution of Klette & Kortum (2004) explains the aggregate growth through firms' R& D investment decisions.[5] In contrast to these studies, in my model, a random process generates all of the new technology, and I do not consider the producers' R&D decisions. However, the knowledge diffusion mechanism that I consider offers an additional explanation through which producer choices lead to productivity growth.

In addition to the baseline framework, the model I set up shares features with other theoretical settings. In my framework, entrants imitate the incumbent technologies as in Luttmer (2007). However, the feature that distinguishes my framework from Luttmer's

[4] see, e.g., survey article by Buera & Lucas (2018)

[5] For recent contributions see e.g. Akcigit & Ates (2019, 2021), Acemoglu & Akcigit (2012) and Akcigit & Kerr (2018).

(2007) is that in my model, incumbents can imitate each other if they successfully implement a technology that a worker introduces. The possibility of learning through hiring gives individual firms control over their future productivity. Gabler & Poschke (2013) consider a similar feature in the Hopenhayn & Rogerson (1993) baseline framework. The authors extend the framework by adding the possibility of investing in experimentation. The mechanism's operating principle shares similarities with my framework as establishments' choices can affect the evolution of their productivity. However, in their paper, the firms draw the experiment's outcome from exogeneous distribution, which separates their work from this paper, where the distribution from which incumbents obtain new technologies is an equilibrium object.

My theoretical framework relies heavily on the fact that workers can convey knowledge between firms. The empirical connection between hiring and firms' productivity growth has been documented by Parrotta & Pozzoli (2012) and Stoyanov & Zubanov (2012). I base my empirical work on Stoyanov & Zubanov's (2012) approach and find similar results. On a related matter, Jarosch, Oberfield & Rossi-Hansberg (2021) study, whether less knowledgeable workers learn from coworkers, and they show that a significant part of workers' compensations stems from learning from coworkers in the same team. While my approach abstracts from wage heterogeneity and does not focus on team-level peer effects, the observations support the view that workers pass on knowledge.

2 Empirical Motivation for the Key Mechanism

The section provides empirical evidence that knowledge diffuses through hiring using a matched employer-employee dataset. The first item of evidence comes from the observation that establishments hiring employees from their more productive counterparts tend to be more productive, on average, in the following period. Additionally, the productivity increase appears to be persistent as it lasts for at least four years after hiring.

2.1 Data

I conduct the empirical analysis with matched employer-employee data from Finnish manufacturing between 1995–2012. The dataset comprises separate employer and employee components, which I merge for the analysis. The employee dataset contains annual information on all Finnish individuals and includes a unique employer identifier for the population's subset. The identifier determines the employer of the individual in the last week of the year. Using the identifier, I link the individual-level information with employer information. The employer information is on the establishment-level and contains annual observations on all firms with at least 20 employees from the manufacturing sector. Hence, the dataset also includes establishments with less than 20 employees. With the dataset, I can track the workers' movements and identify the characteristics of their employers. However, the frequency of the data and how the employer identifier is determined means that a job-to-job transition might involve a period of unemployment, which cannot be observed.

In addition to directly observable characteristics of an establishment, a central variable in the following analysis is the establishment's productivity. I define it as the logarithm of the value-added per employee from various alternatives because the definition is well established and has relatively low data demand. Stoyanov & Zubanov (2012) consider the same measure, and, following their work, I also normalize the measure by removing the 3-digit industry and year effects. I provide a more detailed description of the dataset and descriptive statistics of the variables in Appendix A.

2.2 Measuring Knowledge Spillovers

To analyze the knowledge diffusion through hiring, I need to specify the knowledge spillover measure. The measure aims to capture the establishment's exposure to the new knowledge from the new workers' sending establishments. I define the measure as the average difference between the receiver establishment's and sender establishments' productivity in the last period multiplied by the receiving establishment's share of hires. The definition follows Stoyanov & Zubanov (2012) and can be formally expressed as

$$\varphi_{i,t} = \frac{\sum_{j=1}^{h_{i,t}} (z^s_{j,t-1} - z^r_{i,t-1})}{h_{i,t}} \frac{h_{i,t}}{n_{i,t}}, \tag{1}$$

where z^s_{t-1} and z^r_{t-1} are the normalized productivities of the sending and receiving establishment, $h_{i,t}$ is the number of hired workers, and $n_{i,t}$ is the employment in the receiving establishment. A larger value of the $\varphi_{i,t}$ means a higher knowledge content of the new workers in net terms.

To account for possibly offsetting knowledge spillovers, I decompose the knowledge spillover measure. Making a decomposition gives a more accurate description of the spillovers' nature because the net spillover measure might be zero for two reasons. First, it can be zero if the establishment does not hire or its hired workers are from the same productivity level. Second, the net spillover can be zero if the establishment hires, for example, one worker from a ten percent more productive establishment and one from a ten percent less productive. The decomposition allows me to separate the first and the second case. I do the decomposition by calculating the spillover measure separately for hired workers from more and less productive establishments, and the formal definitions of the two components are

$$\varphi_{i,t}^{+} = \frac{\sum_{j=1}^{h_{i,t}} \mathbb{I}[(z_{j,t-1}^{s} - z_{i,t-1}^{r}) > 0](z_{j,t-1}^{s} - z_{i,t-1}^{r})}{h_{i,t}} \frac{h_{i,t}}{n_{i,t}} \tag{2}$$

$$\varphi_{i,t}^{-} = \frac{\sum_{j=1}^{h_{i,t}} \mathbb{I}[(z_{j,t-1}^{s} - z_{i,t-1}^{r}) < 0](z_{j,t-1}^{s} - z_{i,t-1}^{r})}{h_{i,t}} \frac{h_{i,t}}{n_{i,t}}, \tag{3}$$

where $\mathbb{I}$ is an indicator function.

The spillover measures only describe the knowledge content of hired workers who come from the manufacturing sector. The variables have a high data demand as I need to observe the receiving establishment's productivity and all the sending establishment's productivities. The available data only contains information on the productivities of establishments in the manufacturing sector. Therefore, I cannot calculate the spillovers originating, for example, from establishments in the service sector.

2.3 Descriptive Evidence of Hiring as a Channel of Knowledge Diffusion

Figure 1 shows the connection between establishment growth and the knowledge spillover measure. To obtain an idea of the potential connection, I report several summary statistics that describe the underlying data. The dots present the mean growth at each interval specified by the vertical lines. I also include two different fits: linear and spline. The purpose of the spline fit with four basis functions is to reveal the nonlinear connection between the variables.

The main finding from the results reported in Figure 1 is that establishments with

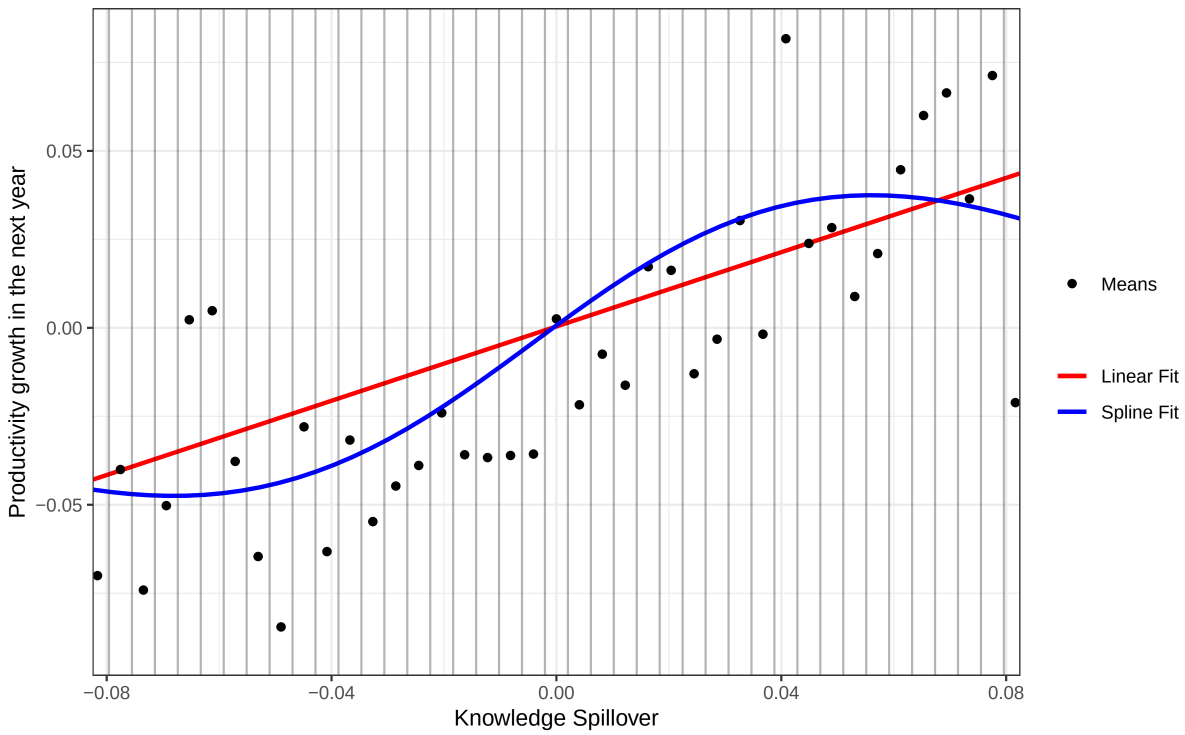

Figure 1: Establishment productivity growth and knowledge spillover.

more knowledge spillovers tend to display larger average growth rates. Moreover, the association does not appear to be linear, and the marginal benefit from an additional unit of spillover seems to decline. This indicates the there can be a saturation point for new knowledge, and hence, establishments cannot absorb more knowledge. The saturation can arise from the increasing difficulty or cost of adopting new technologies.

In the reported spline fit that describes the association between spillovers and establishments' growth, the establishments that hire workers from their less productive counterparts appear to experience productivity losses. These peculiar findings call for further exploration. Therefore, I set up a reduced linear model and estimate it by controlling for establishment and worker characteristics. The estimation shows that the connection between positive spillovers and productivity gains is robust. Moreover, it shows that the link between negative spillovers and productivity decreases is not statistically significant.

2.4 Reduced Form Model of Knowledge Diffusion through Hiring

To explore whether the descriptive evidence section's findings are robust to control variables, I estimate a linear regression model:

$$z^r_{i,t+1} = \beta\varphi_{i,t} + \mathbf{z}^r_{i,t}\alpha_1 + \mathbf{y}_{i,t}\alpha_2 + \mathbf{x}^1_{i,t}\alpha_3 + \mathbf{x}^2_{i,t}\alpha_4 + \epsilon_{i,t+1}. \tag{4}$$

The main variables of interest in the regression model are the receiver establishment's productivity, z^r, and the knowledge spillover measure φ. In addition to the main variables of interest, I include a set of control variables. The current and lagged productivities of the receiver establishment form the first vector of control variables, $\mathbf{z}^r_{i,t}$. The second vector of controls, $\mathbf{y}_{i,t}$, includes the establishment characteristics. Third, I include two vectors of worker characteristics as controls separately for the incumbent, $\mathbf{x}^1_{i,t}$, and new workers, $\mathbf{x}^2_{i,t}$. Finally, all regressions include the average size of sending establishments and year-municipality-industry fixed effects.

The control vectors include several variables that potentially correlate with future productivity. First, the vector of current and lagged productivities contains four lags of productivity. To accompany the productivity information, I include a vector of the establishment's other characteristics. The vector consists of the number of workers, the amount of investment, and the share of hired and separated workers. On the worker side, I use the incumbent and new workers' attributes separately and summarize them with averages for each establishment. The observable worker-level demographic attributes include age, gender, and education. On top of the demographic attributes, I add the logarithm of wages and the proxy for experience. The proxy for experience denotes the number of years after obtaining the most recent degree. These variables control to some extent the workers' productivity, which could bias the results. For the same reason, I calculate the set of controls for incumbent and new workers separately.

Despite the rich set of control variables, some concerns of endogeneity still exist because the reason for hiring is unobservable. More specifically, the concern arises from the fact that establishments may be hiring because they know that they will be more productive in the next period. If this is the case, then the negative and positive spillover components would correlate with future productivity as the source of the workers' would

Table 1: Effect of Spillovers Measure on Productivity

	Dependent variable:							
	Next Period's Productivity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{φ}	0.157**		0.160**		0.167**		0.180**	
	(0.077)		(0.077)		(0.077)		(0.077)	
β_{φ^-}		−0.0004		−0.086		−0.100		−0.015
		(0.103)		(0.105)		(0.105)		(0.106)
β_{φ^+}		0.353***		0.463***		0.497***		0.418***
		(0.116)		(0.117)		(0.117)		(0.119)
$\mathbf{y}_{i,t}$	No	No	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{x}^1_{i,t}$	No	No	No	No	Yes	Yes	Yes	Yes
$\mathbf{x}^2_{i,t}$	No	No	No	No	No	No	Yes	Yes
Observations	132,517	132,517	132,517	132,517	132,517	132,517	132,517	132,517
R^2	0.464	0.464	0.465	0.465	0.465	0.466	0.466	0.466

Notes: *p<0.1; **p<0.05; ***p<0.01. All specifications include industry-municipality-year fixed effects, the average size of sending firms, and four lagged productivities as controls. Robust standard errors in parentheses are clustered at the firm level. The period covered is 1995–2012.

not matter. However, if the positive spillover component only correlates with future productivity, it is more likely that the workers transmit knowledge affecting productivity in the future. Therefore, decomposing the spillover can alleviate the endogeneity concern to some extent.

2.5 Results from the Reduced Form Model

The estimation results in table 1 suggest a connection between the knowledge spillover measure and future productivity. First, in all regression specifications, the net knowledge spillover is positively and statistically significantly associated with future productivity. Moreover, when I decompose the net knowledge spillover into negative and positive components. The positive component remains statistically significant and has a positive connection to the next period's productivity. However, unlike the positive component, the negative component turns out to be statistically insignificant in all specifications.

The connection between the knowledge spillover measure and future productivity appears to be robust as it stays relatively intact when I gradually increase the set of controls. In columns 1 and 2, I only control the sending establishments' average size and the current and lagged productivities. Then, I add into the regression the establishment characteris-

Table 2: Effect of Spillover Measures on Productivity with Different Productivity Leads

	Dependent variable:							
Productivity in	$t+1$	$t+2$	$t+3$	$t+4$	$t+1$	$t+2$	$t+3$	$t+4$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{φ}	0.180**	0.274***	0.072	0.081				
	(0.077)	(0.092)	(0.108)	(0.122)				
β_{φ^-}					−0.015	0.177	−0.168	−0.098
					(0.106)	(0.132)	(0.146)	(0.169)
β_{φ^+}					0.418***	0.392***	0.368**	0.304*
					(0.119)	(0.133)	(0.162)	(0.180)
$\mathbf{y}_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{x}^1_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{x}^2_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,517	114,644	98,573	84,146	132,517	114,644	98,573	84,146
R^2	0.466	0.384	0.335	0.300	0.466	0.384	0.335	0.300

Notes: *p<0.1; **p<0.05; ***p<0.01. All specifications include industry-municipality-year fixed effects, the average size of sending firms, and four lagged productivities as controls. Robust standard errors in parentheses are clustered at the firm level. The period covered is 1995–2012.

tics in columns 3 and 4, the incumbent workers' characteristics in columns 5 and 6, and the new workers' characteristics in columns 7 and 8. Introducing the controls brings some slight variation into the spillover multipliers, which indicates that we cannot analyze the effect of knowledge spillovers reliably without these control variables.

To interpret the regression multipliers in Table 1, we can use a back-of-the-envelope calculation. For example, if we think about an establishment hiring 10 percent of its workers from 10 percent more productive establishments, then on average, the productivity will increase by 0.4 percent ($0.419 \cdot 0.1 \cdot 0.1 = 0.00419$). Subsequently, if the same establishment reduces the hiring from 10 to 5 percent, the productivity gain decreases to 0.2 percent. Similar reasoning applies to all spillover coefficients in Table 1.

According to Table 2, the connection between the knowledge spillover measure and productivity seems persistent. It's because the multiplier stays relatively stable when I explore the connection between the positive knowledge spillover measure and change the dependent variable to different leads. Columns 6-8 report the results for the exploration, and column 5 provides the results from Table 1 as a reference point. From the results, we observe a slight decrease in the value of the multiplier. However, the connection is statistically significant and positive for all leads, indicating that hiring from more productive establishments can give a persistent boost to the establishment's productivity. By repeating the same exploration for the net knowledge spillover in columns 1-4, we can see that the net spillover is statistically significantly connected for two leads, and then the effect disappears. The findings for the net spillover highlight the importance of considering the decomposed measure.

The above findings are not specific to Finland, as the literature reports similar results for other countries. For example, Stoyanov & Zubanov (2012) find similar results by using Danish data. Even if my estimates differ slightly in magnitude from theirs, the connection appears robust between the two countries.

The estimation results show that the observation from the descriptive figures is maintained with a richer econometric specification, which gives us a reason to explore knowledge diffusion through hiring further. So far, the exploration has concentrated on the establishment-level effects while leaving the aggregate importance in the background. To understand the aggregate significance, we need to impose more structure. A structural framework allows us to analyze, for example, what would happen if the knowledge would not diffuse in the economy. We cannot analyze such a question with the reduced form linear model as it does not account for behavioral and distributional changes that knowledge diffusion causes.

3 Model with Knowledge Diffusion through Hiring

To analyze the aggregate significance of knowledge diffusion through hiring, I set up a general equilibrium model in which knowledge diffuses through hiring. The endogenous growth version of Hopenhayn & Rogerson's (1993) model in Poschke (2009) acts as the starting point for the general equilibrium model, and I expand it with a knowledge diffusion component in the spirit of Lucas (2009), Perla & Tonetti (2014), and Lucas & Moll (2014). The diffusion of knowledge occurs in the model because workers learn the productivity of their employer. When the workers move to a new workplace, they can pass on the knowledge. The workers' ability to impart knowledge shapes the establishments' decisions, further affecting the distribution of the establishments and aggregate outcomes.

3.1 Establishments

Incumbents. The aggregate outcomes depend on the choices made by an endogenous mass of incumbent establishments that are heterogeneous in their productivity and number of workers. By discounting the future at rate β, incumbents maximize their expected sum of profits. Incumbents can affect the stream of profits by choosing the labor adjustment and whether to continue. For the choices, relevant state variables are the incumbent's productivity, z_t, and the number of employees at the beginning of the period, n_{t-1}. Incumbents make the choices after δ share of the workers have left the establishment at the beginning of the period. The productivity determines incumbents production possibilities as they produce using technology $f(z_t, n_t) = \exp(z_t)n_t^{\alpha}$, where $0 < \alpha < 1$. The incumbents sell the produced output at a price p and generate revenue $pf(z_t, n_t)$.

In each period, incumbents face costs that they have to pay from the generated revenue. The first cost that establishments have to pay is the fixed operating cost, c_f. The second cost is the wage compensations paid to the workers, $w_t n_t$. The third cost is related to the labor adjustment, $c(n_t, n_{t-1})$. By deducting the costs from the sold output, we can recover the periodical profits, π.

In addition to the periodical profits, incumbents consider expectations about the future. When incumbents choose a profit-maximizing number of workers in a current period, they also impact their expected future as the labor adjustment costs depend on the number of workers. Moreover, if the establishment chooses to hire, $h_t = \max\{n_t - (1-\delta)n_{t-1}, 0\}$, it also affects its expected productivity. The expected productivity changes because of the potential spillovers from new workers, χ_t.

The spillover potential depends on three endogenous factors: the employment at the beginning of the period, the number of hires, and their knowledge distribution, $F_t(z)$. The factors jointly determine the probability of attaining a fixed amount of spillover, η. Workers who come from establishments that are more productive than $z_t + \eta$ can generate the spillover. The assumption that all workers from more productive establishments can improve productivity with constant factor η implies capacity constraint for the new knowledge. The capacity constraint means that even if workers come from the most productive establishment, they can only transmit a η amount of knowledge. In other words, hiring from Amazon's establishment will not make your establishment equally productive, but instead, you might learn better practices in some tasks. Because of the spillover potential, the establishment's workers are temporarily heterogeneous in their knowledge levels after the establishment chooses to hire. More specifically, $[1-F_t(z_t+\eta)]h_t$ of the establishments workers have disposable knowledge.

In each period, hiring establishments try to implement new knowledge brought by workers. To implement new knowledge, establishments choose one worker from their pool of workers at random and then face uncertainty about whether the implementation is successful. If the establishment chooses a hired worker that has arrived from a more productive establishment, the implementation succeeds with probability ψ. By bringing all the elements together, we can write the endogenous part of the establishments' productivity process as

$$\chi_t(h_t, n_t, F_t(z_t)) = \begin{cases} \eta, & \text{with probability } \psi[1 - F_t(z_t + \eta)]h_t/n_t \\ 0, & \text{with probability } 1 - \psi[1 - F_t(z_t + \eta)]h_t/n_t. \end{cases} \tag{5}$$

In addition to the endogeneous part, idiosyncratic shocks affect the establishments productivity. The shocks, u_t, are drawn from a normal distribution $N(0, \sigma_u^2)$. The shocks, spillovers and current productivity together define the next periods productivity

$$z_{t+1} = z_t + \chi_t(h_t, n_t, F_t(z_t)) + u_t, \qquad u_t \sim N(0, \sigma_u^2). \tag{6}$$

A noteworthy feature of the productivity process is that it follows a random walk without the spillover component. The random walk feature is a central element of the mechanism that generates the residual growth that cannot be attributed to the knowledge diffusion through hiring.

By taking stock of all the elements, we can write down the incumbents' problem in a value function form. The incumbents' value function is

$$V(z_t, n_{t-1}) = \max_{x_t} \pi(z_t, n_t, n_{t-1}) + \beta \max\{\mathrm{E}_t[V(z_{t+1}, n_t)], -c(0, n_t)\} \tag{7}$$

$$\text{s.t.} \quad \pi(z_t, n_t, n_{t-1}) = \exp(z_t)n_t^\alpha - w_t n_t - w_t c(n_t, n_{t-1}) - w_t c_{t,f} \tag{8}$$

$$n_t = (1 - \delta)n_{t-1} + x_t, \tag{9}$$

conditional on the knowledge distribution and prices. The solution to the incumbent's problem is a tuple of policy functions $n(z_t, n_{t-1})$ and $y(z_t, n_{t-1})$ describing employment choice and continuation decisions.

From the incumbent's perspective, knowledge diffusion through hiring shapes the establishment's decisions in several ways. First, as hiring enters the establishment's expected productivity, the establishment's optimal size changes. Further, the mechanism makes scaling-up more gradual as it can be more beneficial to keep the hiring positive for a few periods. However, the decreasing returns to scale technology ensures that establishments do not increase their size to infinity. Both behavioral changes are consequences of the knowledge diffusion mechanism and a distinction from a canonical firm/establishment dynamics model.

Entrants. An infinite supply of potential entrants can imitate the incumbents' mean productivity, and evaluate the profitability of entering the market. The entrants compare the expected value of entering the market to the entry costs, $c_{t,e}$. Thus, the free entry condition is

$$w_t c_{t,e} \leq \int V(z_t, 0) G_t(dz). \tag{10}$$

When entrants decide to enter the market, they draw productivity from distribution G. The distribution is a normal distribution with a fixed variance σ_z^2 and a mean, $a_{t,e}$, that follows the incumbents' mean productivity from a distance κ. The mean tracking feature presents the imitation by entrants and is a central feature of the growth mechanism as it sustains the aggregate growth. I discuss the feature in more detail in section 3.4. Additionally, the initial draws generate some of the knowledge, which spreads via the knowledge diffusion mechanism.

3.2 Household

The economy's household maximizes lifetime utility by consuming and supplying labor. Lifetime utility consists of periodically separable utility functions $u(c_t, l_t) = \theta \ln(c_t) - l_t$, where θ it the relative utility parameter. When maximizing lifetime utility, household discounts periodical utilities at a rate of β. Moreover, the maximization problem is subject to a budget constraint $v_t s_{t+1} + c_t = (v_t + d_t)s_t + w_t l_t$. In the budget constraint, the s is the number of shares owned by households as they own all the shares of the active and entering establishments. The shares pay a periodic return of d_t and have a value v_t. The periodic returns is equal to the profits generated by establishments. The solution to households maximization yields an intra-temporal optimality condition $c_t = w_t\theta$ and standard Euler equation $v_t = \beta(v_{t+1} + d_{t+1})(c_t/c_{t+1})$.

3.3 Aggregates and Market Clearing Conditions

Establishment Distribution. To calculate aggregate variables such as labor demand, I need to solve the distribution of establishments. The distribution is a measure of establishments over $\mathbf{x}_t = [z_t, n_{t-1}]$ and it evolves according to a specific law of motion in each period. The first element that describes the evolution of the distribution is the transition matrix $Q_t(\mathbf{X}_{t+1}|\mathbf{x}_t, n_t(\mathbf{x}_t))$. It contains transition probabilities for the incumbent establishments set by the distribution $F_t(z_t)$ and optimal policy $n(z_t, n_{t-1})$. As a distinction from, for example, Hopenhayn & Rogerson's (1993) model, the optimal employment policy also affects transition probabilities on the productivity dimension. By joining the transition matrix that contains the transition probabilities with the entry and exit choices of establishments, we can specify the law of motion for the establishment distribution, $\mu_t(\mathbf{X}_t)$, as

$$\begin{aligned}\mu_{t+1}(\mathbf{X}_{t+1}) = \int (1 - y_t(\mathbf{x}_t))Q_t(\mathbf{X}_{t+1}|\mathbf{x}_t, n_t(\mathbf{x}_t))[\mu_t(d\mathbf{x}_t) \\ + m_t\mathbb{I}(n_t = 0)G_t(dz_t)],\end{aligned} \tag{11}$$

where $\mu_t(\mathbf{X}_t)$ is a measure of establishments in $\mathbf{X}_t$ and m_t is the number of entrants.

By definition, the mean productivity of entrants follows the endogenously determined mean productivity of incumbents. It can be defined formally as

$$a_{t,i} = \int z \left(\int \mu_t(d\mathbf{x}_t)\right)^{-1} \mu_t(d\mathbf{x}_t). \tag{12}$$

The incumbents' mean productivity then fixes the mean of the productivity distribution $G_t(z)$ as they are connected through equation $a_{t,e} = a_{t,i} - \kappa$.

Workers' Knowledge Distribution. The core part of the knowledge diffusion mechanism is the knowledge distribution of reallocating workers. For simplicity, I assume that each reallocating worker remembers their former employer's previous productivity level. Then, the knowledge distribution $f_{t+1}(z)$ is formed by weighting the establishment distribution by the number of workers reallocating from each productivity level:

$$\int f_{t+1}(dz)f_{t+1}(z) = \int [\mathbb{I}(n_{t+1}(z_{t+1}, n_t(\mathbf{x}_t)) - \delta n_t(\mathbf{x}_t) < 0)|n_{t+1}(z_{t+1}, n_t(\mathbf{x}_t)) - \delta n_t(\mathbf{x}_t)|$$
$$q(z_{t+1}|\mathbf{x}_t, n(\mathbf{x}_t))(1 - y_t(\mathbf{x}_t)) + n_t(\mathbf{x}_t)y_t(\mathbf{x}_t)]\mu(z_t, dn_{t-1})$$
$$+ \delta \int n_t(\mathbf{x}_t)q(z_{t+1}|\mathbf{x}_t, n(\mathbf{x}_t))(1 - y_t(\mathbf{x}_t))\mu(z_t, dn_{t-1}) \tag{13}$$

where $n_t(\mathbf{x}_t)$ is the establishments' optimal employment level characterized by z_t and n_{t-1}. The knowledge distribution feeds back to the individual establishments' choices through general equilibrium. The feedback link makes the Markov chain that describes the evolution of incumbent establishments productivities interactive as changes in distribution impact the behavior of establishments and their behavior shapes the distribution.[6]

Labor Market Clearing. Households determine the labor supply and establishments the labor demand; these two must coincide in the equilibrium. To recover the household's labor supply, I impose the asset market clearing, which states that $s_{t+1} = s_t = 1$ in each period. It implies that household's supply of labor is $l_t = \theta - d_t/w_t$. Correspondingly demand for labor is set by the establishments. By utilizing the establishment measure $\mu(\mathbf{x})$, establishment demand for labor is

$$\bar{n}_t = \int n_t(\mathbf{x}_t)\mu_t(\mathbf{x}_t) + c_{t,f}\int \mu_t(\mathbf{x}_t) + \int c(n_t(\mathbf{x}_t), n_{t-1})\mu(\mathbf{x}_t) + c_{t,e}m_t. \tag{14}$$

Correspondingly, we can define aggregate profits, $\bar{\pi}$, which are equal to d, as

$$\bar{\pi}_t = \int \pi(z_t, n_t(\mathbf{x}_t), n_{t-1})\mu_t(\mathbf{x}_t) - c_{e,t}m_t. \tag{15}$$

By equating the defined demand and supply, we get the labor market clearing $\bar{n}_t = l_t$.

3.4 Balanced-Growth Equilibrium

Before defining the balanced-growth equilibrium, I describe the competitive equilibrium of the economy. The competitive equilibrium, where I normalize the price of consumption good to unity, consists of sequences of (1) optimal policies, $\{n_t(z_t, n_{t-1}), y_t(z_t, n_{t-1})\}_{t=0}^{\infty}$, of incumbent establishment (2) wages $\{w_t\}_{t=0}^{\infty}$, (3) establishment distributions $\{\mu_t(z_t, n_{t-1})\}_{t=0}^{\infty}$,

[6] See, for example, Köning et al. (2017) for a theory of innovation and imitation with interactive Markov chain.

and (4) the masses of entrants $\{m_t\}_{t=0}^{\infty}$. These elements satisfy the following conditions: optimal policies are the solution to the incumbent establishment's problem, wages are such that free entry condition is met, distribution follows its law of motion, and the labor market clears.

In what follows, I will only consider the balanced growth equilibrium.[7] I define the balanced growth equilibrium as a competitive equilibrium in which aggregate productivity, consumption and output, and wages grow at a constant rate g. Additionally, establishment productivity distribution's shape will remain invariant. However, it will scale up in steps of g, in logs, every period.

I stationarize the balanced growth equilibrium by transforming growing variables according to $\hat{z}_t = z_t e^{-gt} = z$ and constant variables according to $\hat{x}_t = x_t = x$. This transformation implies that the establishment productivity process will acquire a negative drift equal to g. This negative drift makes the transformed productivity a relative measure of productivity, and, in each period, the establishment's relative position will deteriorate by the amount of g.

3.5 Sources of Aggregate Growth

Knowledge diffusion through hiring is a partial determinant of the rate of aggregate growth in the economy. The knowledge diffusion mechanism directly increases the average productivity as some establishments obtain knowledge spillover in each period. The size of the increase is an equilibrium object which depends on the worker reallocation in the economy. The first source of worker reallocation is the exogenous separation rate of workers. It describes worker movement, which is due to, for example, moving to another city and hence changing employer. The second source of worker reallocation is the job creation and destruction by the establishments. Finally, the exit and entry of establishments create the rest of the worker reallocation. All these sources together form the total reallocation, which fuels knowledge diffusion.

The aggregate growth results from establishment selection and idiosyncratic shocks in addition to the knowledge diffusion across incumbents. As the productivity process is not mean reverting, the establishment productivity distribution's variance increases every

[7] More detailed discussion about the type of equilibrium that I consider can be found from Poschke (2009).

period. The increase in the variance drives some establishments to the exit threshold, which truncates the productivity distribution from the left. The truncation and the increase in the variance together imply that the average productivity increases.

The imitation by entrants sustains aggregate growth. The imitation ensures that entrants maintain with the average productivity increases generated by the knowledge diffusion mechanism, idiosyncratic shocks, and selection. Without the imitation feature, the productivity distribution of establishments would thin out over time. Therefore, imitation forms an essential part of the growth mechanism.

By considering selection and imitation and the knowledge diffusion mechanism, we can see how growth will depend on all of these forces. The exit threshold's location, size of the idiosyncratic shocks, the standard deviation of entrants' productivity distribution, and possible knowledge spillovers mainly determine the increase in incumbents' mean productivity responsible for the aggregate growth. First, the exit threshold's location acts as a truncation point, and a rightward shift in the exit threshold leads to a more substantial increase in mean productivity. Second, a higher variance of the idiosyncratic shocks spreads the productivity distribution proportionally more and, hence, the right tail of the distribution escapes further, indicating a more sizeable increase in mean productivity. Third, we can use similar reasoning, as with the variance of idiosyncratic shocks, for the standard deviation of the entrants' productivity distribution. Finally, the knowledge diffusion mechanism increases the productivity of some establishments. Hence, more frequent and considerable spillovers lead to a starker increase in mean productivity.

4 Quantitative Results

In this section, I assess the quantitative significance of the knowledge diffusion mechanism. I calibrate the model by utilizing the spillover estimates and central moments of establishment dynamics. Based on the calibrated model, knowledge diffusion through hiring increases the aggregate productivity growth by 0.14 percentage points. Moreover, knowledge diffusion increases the household's welfare by 2.6 percent and the adverse effect of firing costs by a factor of 1.2–3.

4.1 Model Calibration

To fit the model to the same data as in the empirical section, I calibrate the parameters. I internally calibrate a set of parameters by simulating the model to recover central moments of establishment dynamics and finding a parameter vector that minimizes the distance between the model and empirical moments. For the rest of the parameters, I find a calibration externally based on commonly used values in the literature or calculating them directly from the microdata.

First, I externally calibrate the production function's curvature, the discount rate, and the utility function parameter. For the production function curvature, α, I use the value of 0.64 to match the average labor share. Annual calibrations typically use 0.95 as the discount rate, β, and I follow this convention. The utility function parameter, θ, fixes the aggregate expenditure because the labor supply is fully elastic. I will normalize its value equal to unity, as I am interested in the relative figures in terms of aggregate variables rather than absolute levels. Additionally, I normalize the mean of the productivity distribution of entrants to zero.

Second, I calibrate the firing costs externally by using the OECD data.[8] The Employment Protection Legislation (EPL) data from OECD reports the lengths of the notice periods for workers in Finland. The OECD database also reports tenure distribution for workers in Finland, with a rough classification. By utilizing both data sources, I can obtain a rough estimate of the costs of firing a worker in Finland, which is 27 percent of the annual hours.[9] Because an individual worker supplies a constant amount of labor, the value translates directly as wages in the model and fixes the parameter λ equal to 0.27 in the firing cost function, $c(n_t, n_{t-1}) = \lambda|\min\{n_t - (1-\delta)n_{t-1}, 0\}|$.

Third, the average replacement hiring rate for establishments that do not create or destroy jobs fixes the exogenous separation rate δ. I calculate the average replacement hiring rate from the data as the data allows me to observe workers' movement separately from the changes in an establishment's employment. To recover the average replacement hiring rate, I filter out all establishments that change their size and calculate the average replacement hiring rate for the remaining establishments. In the model, all hiring done

[8]I use OECD data instead of the microdata from the second section because, in that dataset, I cannot calculate tenure reliably. Another reason is that OECD data has information for several countries, which enables the extrapolation of results.

[9]I report the details of the calculation in Appendix A

Parameter	Value
c_e	68.823
c_f	0.314
σ_u	0.125
σ_z	0.726
κ	0.320
η	0.016
ψ	0.656

Table 3: Calibrated parameter values.

by establishments that do not change their employment is due to replacement hiring set by δ. Therefore, δ can be directly attached based on the data moment, which equals 0.0839.

I target seven empirical moments in the Finnish data with the remaining seven parameters in the internal calibration. More specifically, the seven parameters are the distance between mean productivities of entrants and incumbents κ, the standard deviation of the entrant distribution σ_z, the standard deviation of the productivity shock of incumbents σ_u, the entry cost c_e, the fixed operating cost c_f, the success probability of implementation ψ, and the spillover quantity parameter η. I use these parameters to target the average aggregate growth between 1995–2012, the share of employment in establishments under the mean size, the average annual turnover between 1995–2012, the mean size of establishments, match the entry rate of establishments, the share of establishments hiring from the manufacturing sector, and the spillover coefficient in Table 1 Column 7.

I provide a heuristic argument on the most informative moments to each parameter because the moment matching jointly determines the parameters. The joint determination of the parameters is a consequence of the complex structure of the model. I divide the parameters into two groups: the knowledge diffusion mechanism related parameters and the reminder. The spillover κ and the probability of implementing new knowledge η form together the first group.

First, the spillover coefficient and the proportion of establishments hiring from the manufacturing sector determine the knowledge diffusion mechanism related parameters. For each value of η, estimating a model $\ln(y_{i,t+1}/n_{i,t+1}) = \beta_0 + \beta_1 \mathbf{x}_t + \beta_2 \varphi^+_{i,t} + \epsilon_{i,t}$, where $\mathbf{x}_t$ is the set of controls containing current and lagged productivities, hiring share, and

Moment	Data	Model
Entry Rate (%)	3.84	3.55
Mean Size	19.65	19.74
Share of Employment in Establishments Under the Mean Size (%)	16.20	15.25
Turnover (%)	15.29	16.08
Spillover Coefficient	0.42	0.42
Share of Hiring Establishments with Positive Spillover (%)	10.88	11.06
Aggregate Growth (%)	2.56	2.56

Table 4: Empirical fit.

separation share, from simulated data will yield a different β_2. Hence, the goal is to match the β_2 as closely as possible to the estimated coefficient from the data. Moreover, I use the percentage of establishments with a non-zero value for the spillover variable from all hiring establishments to inform the parameter ψ. I select the target because some establishments lack the spillover variable's value, even if they are hiring. The lack of the spillover variable indicates that the establishments did not hire anyone from the manufacturing sector. For the spillover coefficient target to work, I need to have the same share of zeros for the spillover variable in the simulated data as in the actual data. Hence, I calculate the spillover measure for establishments only when the implementation is successful.

Second, I argue that the rest of the parameters can be informed as follows. If the entrants' average productivity is close to the incumbents' average productivity, the economy will grow more rapidly when keeping all other things equal. Therefore, the average growth of output is informative about the parameter κ. The average employment of establishments depends on the entry costs because any change in the parameter directly affects the equilibrium wage rate, which then impacts the establishments' employment policies. Simultaneously, the entry distribution's standard deviation determines how employment is distributed around a given mean size. Hence, the entry cost c_e, and the standard deviation of the entrant distribution σ_z are jointly informed from the mean size of establishments and the share of employment in establishments under the mean size. The job creation and destruction process of incumbents' mainly depends on the value of σ_u. Thus, I will inform this parameter from the average turnover in the economy. The fixed operating costs have a direct impact on the exit threshold of establishments. As

Variable	Twofold Spillovers	Calibrated Model	Without Spillovers
Average Establishment Size	17.26	19.74	20.14
Establishment Employment Under 50 (%)	94.90	94.68	94.61
Establishment Employment Over 50 and Under 250 (%)	4.18	4.27	4.30
Establishment Employment Over 250 (%)	0.92	1.05	1.09
Mean Growth Rate (%)	4.54	2.44	1.31
Std of Growth Rates (%)	61.00	47.32	45.03
Turnover (%)	20.25	16.08	14.82
Entry Rate (%)	3.36	3.55	3.54
Firm Mass	110.86	100.00	95.16
Aggregate Growth (%)	2.79	2.56	2.42
Output/Wage	98.88	100.00	100.17
Employment	99.48	100.00	100.03
Compensating Consumption Change	3.53	0.00	-2.56

Table 5: Changes in the degree of technology diffusion across incumbents. I scale the output, firm mass, and employment to 100 in the benchmark economy, and report other corresponding values as relative numbers.

the entry and exit rates will be equal at the equilibrium, the entry rate informs us about fixed costs.

Table 3 displays calibrated parameter values, and Table 4 shows targeted data moments together with an empirical fit. From the parameters that give the best empirical fit, we can observe that entering the manufacturing sector costs the equivalent of a wage paid for 69 years to a single worker. Running the establishment entails the cost of a wage paid for four months to a single worker. Overall the empirical fit is good, and the most important characteristics, namely the aggregate growth and the spillover coefficient, give an exact match.

4.2 Quantitative Significance of Knowledge Diffused by Workers

The main results, reported in Table 5, reveal that knowledge diffusion through hiring has a quantitatively significant impact. We can conclude this from two central findings. First, the knowledge diffused by workers increases the aggregate growth rate by 0.14 percentage points. Second, the welfare of the household increases by 2.56 percent because of knowledge diffusion. I find both results by comparing the calibrated economy to a hypothetical economy without knowledge diffusion. As a welfare measure, I use a utility equating consumption changes. It measures the percentage change in consumption for the benchmark economy's consumer which would equate the lifetime utilities between the benchmark economy and the comparison economy.[10] Moreover, the measure helps the comparisons when the growth and level of output simultaneously changes. For example, we can see from Table 5 that the mechanism's level effect is modest and solely considering it would be misleading.

In addition to the growth and welfare effects, the mechanism also significantly affects the central parts of establishment dynamics. One of the central measures describing the establishment dynamics is worker turnover. It increases by 1.3 percentage points when knowledge diffuses through worker reallocation. Additionally, the average growth rate of establishments increases over a percentage point, and the distribution of growth rates widens. An increase in the entry rate accompanies the change in establishment growth rate distribution. The changes confirm the prior expectation that the establishments' environment becomes more dynamic when establishments can learn through hiring.

By comparing the benchmark economy to a hypothetical economy with twofold spillovers in Table 5, we can see that the spillovers' effect is nonlinear. For example, doubling the size of the spillovers cause the output to decrease. However, the welfare measure reveals that the change in the aggregate growth rate compensates for the loss. The finding highlights the importance of using a quantitative framework in analyzing the significance of the spillovers.

The size of the growth effect is in line with the values found in the literature. Even if there is no directly comparable analysis of a similar mechanism, we can compare the effect's size to the previously studied connection between firing costs and growth. Poschke (2009) finds that firing costs that correspond to a one-year wage reduce the growth by 0.09 percentage points. Similarly, Mukoyama & Osotimehin (2019) find a 0.1–0.2 percentage point effect of firing costs depending on the calibration. When compared to both studies, the effect that I find seems to be within reasonable range.

The results show that in an environment with a relatively low level of dynamism, such as the Finnish manufacturing sector, a reasonable share of the growth comes from

[10]This measure can be formally written as

$$\exp\left((1-\beta)\left(\sum_{t=0}^{\infty}\beta^t(\ln(\exp(g_c t)C_c)-N_c)-\sum_{t=0}^{\infty}\beta^t(\ln(\exp(g_b t)C_b)-N_b)\right)\right)-1,$$

where c is the comparison economy and b is the benchmark economy.

Variable	$\lambda = 1$	Calibrated Model	$\lambda = 0$
Average Establishment Size	19.92	19.74	17.84
Establishment Employment Under 50 (%)	94.57	94.68	94.76
Establishment Employment Over 50 and Under 250 (%)	4.36	4.27	4.24
Establishment Employment Over 250 (%)	1.07	1.05	1.00
Mean Growth Rate (%)	3.04	2.44	2.87
Std of Growth Rates (%)	41.86	47.32	71.96
Turnover (%)	11.79	16.08	35.26
Entry Rate (%)	3.35	3.55	3.49
Firm Mass	94.48	100.00	105.14
Aggregate Growth (%)	2.45	2.56	2.66
Output/Wage	100.59	100.00	99.95
Employment	100.82	100.00	100.75
Compensating Consumption Change	−2.05	0.00	1.45

Table 6: The effect of firing costs in the calibrated model. I scale the output, firm mass, and employment to 100 in the benchmark economy, and report other corresponding values as relative numbers.

worker transmitted knowledge. Simultaneously, the results show that the residual growth mechanism explains a large chunk of aggregate growth. The results encourage further exploration of the worker-based diffusion of knowledge and its impact. So far, I have explored the significance of knowledge diffusion from a positive perspective. Because the positive analysis shows that the studied mechanism has a significant impact, I consequently move towards a more normative perspective. Therefore, I explore how knowledge diffusion through hiring changes the firing cost's effect in the following section. Strict employment protection legislation, modeled by the firing cost, is a prominent feature of the Finnish economy, and thus, the current setting is particularly suitable for the analysis.

4.3 The Role of Firing Costs

To see how knowledge diffusion through hiring affects economic policy, I consider the role of firing costs. Based on the previous literature, we already know that the firing costs have a severe impact on output and growth in settings without knowledge diffusion through hiring. In what follows, I show how the impact of firing cost changes when we add the knowledge diffusion mechanism into the mix. Given that the mechanism of interest operates through worker reallocation, any friction limiting workers' movement impairs the knowledge diffusion mechanism.

Firing costs significantly impact the calibrated economy based on the results reported in Table 6. According to the results removing firing costs increases the aggregate growth by 0.1 percentage points and keeps the output level almost intact. Moreover, the welfare impact summarizing both aggregate changes is positive a 1.5 percent. Removing the firing costs also impacts the business dynamism because turnover increases by 19 percentage points, and the establishment growth rate distribution spreads out.

In the hypothetical economy without knowledge spillovers, the firing costs are of less of a concern than in the calibrated economy. According to the hypothetical economy results in Table 7, firing costs do not impact aggregate growth. However, removing the firing costs increases output by 1 percent and welfare by 0.7 percent. Removing the firing costs in the hypothetical economy only increases turnover by 10 percent. Additionally, it spreads the establishment growth rate distribution by only a small amount compared to the calibrated economy. By comparing the effect of firing cost in the calibrated and hypothetical economies, we can see that knowledge diffusion through hiring makes the negative effects twice as large. For example, the firing cost's welfare impact is twice as high in the economy with the knowledge diffusion mechanism.

As an additional exercise, I also consider higher firing costs $\lambda = 1$. I choose the level of firing costs to match the value used in Poschke (2009). Because the model shares similarities with Poschke's quantitative framework and the firing cost level are the same, the results are comparable to some extent. Poschke calibrates his model to U.S. data and finds that introducing firing costs decreases aggregate growth by 0.09 percentage points. I repeat his exercise with the hypothetical economy without spillovers, and the results in Table 7 show that the corresponding growth impact is 0.07 percentage points. Then, when I consider the knowledge diffusion mechanism in Table 6, the corresponding growth impact is significantly higher, 0.21 percentage points. By considering the figures in the Finnish economy, we can make a simple back-of-the-envelope calculation for the U.S. In an economy, without the knowledge spillover, the U.S. suffers 1.3 times more from firing costs. This would indicate a 0.27 percentage point loss in the growth rate with the knowledge diffusion mechanism when directly applied. However, the figure is suggestive as there is no sufficient information available to calibrate the model to the U.S. data.

To summarize, the diffusion mechanism amplifies the negative effect of firing costs on

Variable	$\lambda = 1$	Calibrated Model $\eta = 0$	$\lambda = 0$
Average Establishment Size	20.79	20.14	20.07
Establishment Employment Under 50 (%)	94.59	94.61	94.63
Establishment Employment Over 50 and Under 250 (%)	4.28	4.30	4.27
Establishment Employment Over 250 (%)	1.13	1.09	1.10
Mean Growth Rate (%)	2.11	1.31	0.84
Std of Growth Rates (%)	41.48	45.03	50.97
Turnover (%)	11.66	14.82	23.64
Entry Rate (%)	3.38	3.54	3.54
Firm Mass	96.10	100.00	100.88
Aggregate Growth (%)	2.35	2.42	2.42
Output/Wage	100.06	100.00	100.94
Employment	100.51	100.00	100.42
Compensating Consumption Change	-1.57	0.00	0.68

Table 7: The effect of firing costs in the calibrated model, when shutting down the diffusion of knowledge across incumbents. I scale the output, firm mass, and employment to 100 in the benchmark economy, without spillovers, and report other corresponding values as relative numbers.

the aggregate outcomes by a factor of 1.2–3, depending on the measure. Comparing the aggregate growth rate effect of the high firing costs between calibrated and hypothetical economies yield the largest amplification. In contrast, the smallest amplification arises when we compare the welfare measure's changes in response to the high firing costs. The literature explores the role of firing costs and adjustment frictions to a large extent. In light of the evidence, we might question whether the previously found adverse effects of these frictions are even more severe.

5 Conclusion

I find empirical evidence that links hiring from more productive establishments to the productivity growth of establishments. Motivated by the empirical evidence, I study the quantitative significance of knowledge diffusion through hiring in a canonical firm dynamics framework. By calibrating the framework into central data moments, I show that the knowledge diffusion mechanism significantly impacts aggregate growth and central parts of establishment dynamics. Moreover, the mechanism amplifies the adverse effects of firing costs on aggregate growth and other outcomes.

From the policy perspective, I show that the negative effect of firing costs on aggregate outcomes might be more severe than previously thought. Besides hindering reallocation, firing costs lower the pace of knowledge diffusion. Accounting for this mechanism reveals that the adverse effect of firing costs can be even three times larger. Moreover, while the analysis does not explicitly consider the effect of non-compete contracts, it shows their effect's potential upper limit. That is if the agreements could completely shut down the knowledge flow through worker mobility. A more thorough analysis of the effects of such contracts on aggregate growth would be an interesting avenue for future research, and it would have to take into account the incentives that intellectual property protection creates for innovation.

Throughout the paper, I focus on the establishment dynamics side of knowledge diffusion through hiring. Therefore, I have dedicated fewer details to modeling the labor market. I believe that more detailed modeling of the labor market can offer additional insight into the effects of knowledge diffusion. Moreover, studying the association between hiring and producers' productivity growth with a broader set of countries can deepen our understanding as the current evidence is mainly from Nordic countries.

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Appendix A. Data

Appendix A.1 Detailed Data Description

I construct the dataset by joining together three microdata sets provided by Statistics Finland. The datasets are accessible through an application process. To build the dataset used in the analysis, I combine the establishment-level dataset named Longitudinal Database on Plants in Finnish Manufacturing (LDPM) with individual-level information from two modules of the FOLK dataset: basic and employment.

The LDPM operates as the primary data for the analysis, and I join other information to it. The LDPM contains information from all manufacturing firms with at least 20 employees in a given year between 1995 and 2012. The dataset admits the calculation of each establishment's productivity and contains a rich set of other variables used in the regressions.

The individual-level data (FOLK, modules: income and basic) contains information from each individual from Finland. I use the population dataset to track the movements of workers between manufacturing establishments. The individual-level data includes information on basic demographics, wages, education, and working history.

Appendix A.2 Data Treatment

To remove a small amount of outlier knowledge spillover measures, I exclude all yearly establishment-level observations where the knowledge spillover measure is outside of $[Q_1 - 3 \cdot IQR, Q_3 + 3 \cdot IQR]$, where Q's are the respective quartiles, and IQR is the interquartile range, for the hiring establishments. The exclusion of the observations outside the brackets is the only manipulation done to the final merged dataset.

Appendix A.3 Sample Descriptives

I report the sample descriptives in tables 8 and 9. Statistics Finland permits the extraction of minimum and maximum values. Hence, the tables display only means and standard deviations.

Appendix A.4 Firing Costs in Finland

I approximate the level of firing costs with the average duration of the notice period for workers. I utilize the Employment Protection Legislation (EPL) data and tenure distri-

Variable	Mean	Sd.
Labor Productivity	0.0211	0.598
Net Spillover	−0.000 179	0.0125
Positive Spillover	0.001 36	0.008 76
Negative Spillover	−0.001 54	0.009 32
Sender Establishment Employment	9.64	75.5
Number of Hires	3.24	20.7
Number of Separations	3.32	20.6
Number of Employees	19.7	91.4
Value Added	1 500 000	16 100 000
Investment	216 000	3 380 000
Number of Establishments	36378	

Table 8: Descriptive Statistics of Establishments.

Incumbent Workers			
	Variable	Mean	Sd.
	Wage	10.3	0.537
	Age	42.1	10.7
	Experience	16.1	9.77
	Share of Males	0.725	
	Share with Secondary Degree	0.502	
	Share with Upper Secondary Degree	0.124	
	Share with Tertiary Degree	0.138	
	Share with Doctoral Degree	0.003 75	
	Share with Unknown Degree	0.232	
	Number of Workers	4857435	
Hired Workers			
	Variable	Mean	Sd.
	Wage	9.70	0.947
	Age	32.6	11.8
	Experience	10.3	9.46
	Share of Males	0.712	
	Share with Secondary Degree	0.521	
	Share with Upper Secondary Degree	0.107	
	Share with Tertiary Degree	0.170	
	Share with Doctoral Degree	0.004 62	
	Share with Unknown Degree	0.198	
	Number of Workers	1051327	

Table 9: Descriptive Statistics of Workers.

bution data from the OECD in the approximation. Table 10 contains the information used in the calculations. As we can see, the notice period system and the tenure data do not coincide. Therefore, I assume that the probability mass distributes evenly over the

Notice period system		Tenure distribution	
Tenure in Years	Notice Period in Months	Tenure Bin	% of Workers
≤ 1	0.5	≤ 1 month	5.25
> 1 & ≤ 4	1	> 1 month & ≤ 6 months	6.9
> 4 & ≤ 8	2	> 6 months & ≤ 1 year	6.85
> 8 & ≤ 12	4	> 1 year & ≤ 3 years	13.0
> 12	6	> 3 years & ≤ 5 years	10.3
		> 5 years & ≤ 10 years	17.7
		> 10 years	39.9

Table 10: The Finnish notice period system and tenure distribution.

months in each bin, and as the highest amount of tenure one can have, I use 49 years (64-15). With the assumptions, I obtain the average notice period for a random worker in Finland, which is 0.27 years.

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