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ABSTRACT

I explore the role of knowledge diffusion among producers as a driver of productivity growth. By estimating a reduced form model with Finnish employer-employee data, I find evidence that employing workers from more efficient establishments enhances productivity. To understand the aggregate impact of the finding, I develop an endogenous growth model that incorporates the transmission of knowledge through worker reallocation. The calibrated model reveals that knowledge spillovers can increase aggregate productivity growth by 0.35 percentage points and significantly impact output. Moreover, I establish that this mechanism can exacerbate the adverse impact 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 studies by Poschke (2009) and Mukoyama & Osotimehin (2019) have shown effects are not limited to the levels but can also impact the growth path. Traditionally, when exploring how worker flows aggregate shape 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 the recent growth literature and the wide use of non-compete contracts[3].

Empirical papers of Stoyanov & Zubanov (2012) and Serafinelli (2019) support the idea of workers transmitting knowledge between producers. Specifically, producers who hire workers from their more productive counterparts appear to experience productivity gains. However, while previous studies have shown that knowledge diffusion can lead to productivity improvements at the firm level, it is unclear whether these improvements translate into aggregate gains for the economy as a whole. Therefore in this paper, I develop and calibrate a general equilibrium model where workers can diffuse knowledge across establishments and show that knowledge diffusion contributes significantly to aggregate outcomes and the effects of firing cost.

First, to explore the relationship between worker mobility and productivity in a reduced form, I propose an extension to the control

[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, Restuccia & Tavares (2019), 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 (2023) points out that about 64% of executives in publicly listed firms have signed non-compete contracts.

function approach typically used in production function estimation. By making a marginal change to the assumptions, I can use it to estimate spillovers alongside input elasticities. However, the extended method requires additional information on mobility links across producers to identify the average spillover per hire from a more productive establishment. The advantage of this approach is that it addresses the simultaneity and selection issues that could otherwise compromise the estimation.

The empirical findings support hiring as a channel of knowledge diffusion in the administrative data on Finnish manufacturing establishments. On average, hiring a worker from more productive establishments is connected with a 0.65 percent increase in productivity, indicating positive spillover effects. The result is robust for alternative labor input measures and consistent with previous research with other countries, suggesting that Finland's observed connection is not unique.

Next, to explore the aggregate significance of knowledge diffusion through hiring, I develop a model of establishment dynamics by extending an endogenous growth version of Hopenhayn & Rogerson's (1993) model in Poschke (2009) with a knowledge diffusion mechanism. A key feature of the model is that workers changing employers may retain productivity-enhancing knowledge. When establishments dismiss workers due to idiosyncratic productivity shocks or exit decisions, they become available for hire, and other establishments may hire them to expand or replace dismissed workers. Some new workers may have previously worked for a more productive employer and can pass on their knowledge to the new establishment, leading to productivity gains. From the establishments' perspective, the potential for attaining new knowledge presents an opportunity to enhance productivity by hiring an additional worker and incurring the associated costs of adjustment. The likelihood of establishments benefiting from the knowledge of newly-hired workers depends, in part, 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, indicating that the productivity of some establishments improves while others are forced under the endogenously determined profitability limit. The increase in the variance and the simultaneous left-truncation of the productivity distribution enhance incumbents' mean productivity, leading to aggregate growth. Entrants play a central role in this process as they imitate incumbents' growing average productivity, thereby sustaining economic growth.

I utilize the model's flexibility to isolate the contribution of knowledge diffusion through hiring to aggregate productivity growth. Simultaneously targeting the micro-level spillover estimate and the aggregate growth rate as part of the internal calibration, the model successfully replicates the targeted reduced-form connection between worker flows from more productive units and establishment productivity growth. Additionally, the internal calibration incorporates central moments of establishment dynamics, such as establishment size, job turnover, and entry rate.

To derive the main results, I compare an economy with knowledge diffusion through hiring to a hypothetical one without it. When workers diffuse knowledge, it enhances the growth of low-productive establishments, thereby increasing the overall mean size of establishments by pushing up the left tail of the productivity distribution. These changes, combined with other factors like entry rate and price adjustments, result in a 0.35 percentage point increase in aggregate productivity growth and a 4.3 percent increase in output. Furthermore, according to the compensating variation, consumption in an economy without spillovers would need to be raised by 8 percent to achieve the same level of lifetime utility. The welfare comparison is helpful in that it takes into account the simultaneous changes in output's level and growth.

My findings show that worker-transmitted knowledge significantly impacts a country's growth rate, highlighting the substantial impact labor market policies can have on a country's growth rate. To illustrate this point, I examine the role of firing costs that equal one year's wage. Introducing such firing cost leads to a 3.6 percent decrease in output and a 0.17 percentage points reduction in the growth rate. The equivalent variation amounts to a 9 percent decline. To provide a basis for comparison, I recalibrate the model without the spillover mechanism and repeat the same exercise. In this case, the output decreases by 3.2 percent while the growth rate stays nearly unaffected. The compensating variation, which summarizes the changes, indicates that a 5 percent increase in consumption would be required to offset the firing costs. The results demonstrate that spillovers amplify the negative effects of firing costs by a factor of 1.8.

Related Literature. Several studies have explored the connection between firing costs and the level and growth of aggregate productivity. The literature originates from Bentolila & Bertola (1990) and Hopenhayn & Rogerson (1993). Hopenhayn & Rogerson (1993) find that firing costs reduce aggregate productivity, and subsequent literature has focused on understanding the relationship between firing costs and the level of productivity using a variety of empirical and structural approaches. By explicitly studying the effect of firing costs on aggregate productivity growth, Poschke (2009) finds that a firing tax decreases aggregate growth if it applies to all producers. Mukoyama & Osotimehin (2019) find a similar negative growth effect for labor adjustment costs in their calibration, where innovations from entrants primarily drive aggregate growth. I contribute to the firing cost discussion by demonstrating that considering knowledge diffusion through hiring amplifies the negative impact of firing costs on aggregate growth.

Previous literature has examined the role of knowledge transfer between producers as a source of economic growth.[4] For instance, Perla & Tonetti (2014) and Lucas & Moll (2014) explore producers' time allocation decisions between producing and searching for new ideas. Furthermore, Alvarez, Buera & Lucas (2008, 2013), Perla, Tonetti & Waugh (2021), and Buera & Oberfield (2020) have investigated knowledge diffusion in the context of trade. In their models, producers trade goods and disseminate knowledge, resulting in additional positive effects of trade beyond standard efficiency gains from reallocation. In this paper, I incorporate a similar type of endogenous flow of new ideas, which is now influenced by the hiring policies of establishments and the distribution of their productivities. Furthermore, I demonstrate how knowledge diffusion amplifies the gains from reallocation

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

in the context of firing costs.

The literature stemming from the seminal contribution of Klette & Kortum (2004) analyzes aggregate growth by examining firms' R&D investment decisions.[5] In contrast to these studies, my model assumes that new technology is generated through a random process and does not incorporate producers' R&D decisions. However, the knowledge diffusion mechanism provides an additional explanation for productivity growth arising from producer choices.

Connecting knowledge flows through worker reallocation to aggregate growth has similarities with studies by Sohail (2021), Baslandze (2022), and Engbom (2023) that examine the dynamics of spinouts, which are firms founded by former employees of incumbents, and with Bradley & Gottfries (2022), who explore the relationship between labor market fluidity and aggregate growth through imitation. In this context, worker mobility is crucial in determining aggregate growth. The key difference is that this strand of literature focuses on the sources of firm heterogeneity at the time of entry, which Sterk ⓡ Sedláček ⓡ Pugsley (2021) have shown to form a significant amount of overall firm heterogeneity. My approach complements this research by concentrating on understanding the differences arising after entry partly attributable to worker-transmitted knowledge.

The possibility of learning through hiring provides individual firms with control over their future productivity. Gabler & Poschke (2013) examine a similar mechanism where firms have control over their productivity through investments in experimentation. However, in their paper, the firms draw the experiment's outcome from an exogenous distribution, distinguishing their work from this paper. In this study, the distribution from which incumbents obtain new technologies is an equilibrium object.

My theoretical framework heavily relies on the fact that workers can convey knowledge between firms. Empirical studies by Parrotta & Pozzoli (2012), Stoyanov & Zubanov (2012), and Serafinelli (2019) have documented the connection between hiring and firms' productivity growth in other countries. Among these, Serafinelli (2019) is most closely related to this paper as it also employs the control function approach introduced in

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

Olley & Pakes (1996), Levinsohn & Petrin (2003), and Ackerberg, Caves & Frazer (2015, hereafter ACF) to address simultaneity and selection issues. An important difference is that, instead of predetermining "good" firms and studying how mobility from them contributes to firm productivity, I extend the method of ACF in such a way that input elasticities and spillovers can be determined simultaneously with only information on mobility links.

As this paper focuses on how knowledge transmits from one establishment to another, with workers serving as mere intermediaries, I have dedicated more details to modeling the establishments' hiring, separation, exit, and entry choices. Consequently, I have abstracted from some aspects of human capital heterogeneity across workers. In studies conducted by Gregory (2020), Jarosch, Oberfield & Rossi-Hansberg (2021), Engbom (2022), and Shi (2023), the relationship between individuals' human capital development and employers' characteristics is examined more thoroughly. However, generally in these type of studies, the firm's productivity component, which enhances the efficiency of all workers in a multi-worker firm context, only evolves exogenously.

2 Empirical Motivation for the Key Mechanism

The section presents empirical evidence on knowledge diffusion through hiring using a matched employer-employee dataset. To estimate spillover effects, I propose a method based on the commonly used control function approach for estimating input elasticities of production functions. The results obtained from the proposed estimation method indicate that hiring from a more productive establishment increases productivity by 0.65 percent.

2.1 Estimating Productivity Spillovers with Control Function Approach

First, I define the spillovers through hiring as follows. Let $n_t = \varphi(h_t, s_t, n_{t-1})$ represent the number of employees at time t, where h_t denotes hires and s_t denotes separations. The hires h_t can be decomposed into three components based on whether the worker came from a more productive unit, denoted by h_t^+, a less productive unit, or if the hire was not a job-to-job transition. Then, by assuming the standard Cobb-Douglas production function in logarithmic form with Hicks-neutral productivity z_{it} that follows AR(1) process with drift component, we can express the two central pieces of any producer's decision problem as

$$\ln(y_t) = \beta_n \ln(n_t) + \beta_k \ln(k_t) + z_t \tag{1}$$

$$z_t = \rho z_{t-1} + \beta_z h_t^+ + \vartheta_t. \tag{2}$$

Here, β_z represents the marginal effect of one hire from a more productive unit, ρ represents the autoregressive parameter, ϑ is an error term, and β_k and β_n are input elasticities. Now, we can examine the marginal contribution of hires from more productive units to gain further intuition. By forgetting the capital for a moment and differentiating the above equations with respect to hires from more productive units, taking into account the law of motion for labor, and solving for the spillover multiplier, we obtain:

$$\beta_z = \frac{1}{y_t}\frac{\partial y_t}{\partial h_t^+} - \beta_n \frac{1}{n_t}\frac{\partial n_t}{\partial h_t^+}. \tag{3}$$

The equation makes the definition of spillovers explicit: it is the amount by which hiring from a more productive establishment changes the output when the effect of the input channel is deducted. Note that the above derivation does not describe any producer's economic decision problem completely, but it is useful for understanding the empirical approach.

To estimate the spillover coefficient, I require a proxy for the establishments' productivities as the ranking based on productivity determines whether a hire originated from a 'better' establishment. However, this presents a specific challenge: any productivity measure will depend on the input elasticities of the production function, and any estimation of input elasticities will rely on assumptions about the evolution of productivities, including the potential gains from spillovers. To address this challenge, I leverage the flexibility control function approaches provide. These approaches are well-established solutions to the simultaneity and selection problems that can arise when estimating input elasticities using simple fixed-effects OLS.

I propose a new estimation strategy that jointly identifies input elasticities and spillovers. The success of this method depends on two key features of the control function approach. First, identification is based on the assumption of a first-order Markov productivity process. This assumption allows me to incorporate an additional spillover component into the productivity process, which dependent on the previous period's productivity.[6] Second, the control function provides a productivity ranking of establishments, enabling accurate calculation of worker flows from more productive establishments during estimation.

The goal is to estimate the following set of equations

$$\ln(y_{it}) = \beta_0 + \beta_n \ln(n_{it}) + \beta_k \ln(k_{it}) + z_{it} + \epsilon_{it} \tag{4}$$

$$z_{it} = \rho z_{it-1} + \beta_z h^{+}_{it}(z_{it-1}, \mathbf{z}_{t-1}) + \vartheta_{it}, \tag{5}$$

where ϵ_{it} represents an error term that does not influence input choices. The variable z_{it} is the time-varying productivity that can affect the producers' input decisions. For clarity, I denote the hires from more productive establishments as dependent on the overall set of productivities in the economy.

First, I specify the same assumptions as in the ACF to estimate the production function and productivity process specified above.[7] Given these assumptions and as discussed in the ACF, the production function parameters can be estimated in the following way. First, the assumptions imply that the intermediate input function, $m_{it} = f(k_{it}, l_{it}, z_{it})$, can be inverted with respect to z_{it} leading to

$$z_{it} = f^{-1}(k_{it}, l_{it}, m_{it}). \tag{6}$$

[6]This detail makes the control function approach more suitable for my purposes comparison to the panel data approaches introduced in Chamberlain (1982), Anderson and Hsiao (1982), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998, 2000) that are another approach to tackle the identification problems in the production function estimation.

[7]Appendix A contains the basic set of assumptions.

Substituting the function for productivity into Equation (4) yields,

$$\ln(y_{it}) = \beta_0+\beta_n \ln(n_{it})+\beta_k \ln(k_{it})+f^{-1}(k_{it}, l_{it}, m_{it})+\epsilon_{it} = \Psi(k_{it}, l_{it}, m_{it})+\epsilon_{it}, \tag{7}$$

which can be used to obtain estimate $\hat{\Psi}_t(k_{it}, l_{it}, m_{it})$ either nonparametrically or by using polynomial approximation. Using the estimated $\hat{\Psi}_t$, the estimate for productivity can be obtained

$$\hat{z}_{it}(\beta_l, \beta_k, \beta_0) = \hat{\Psi}(k_{it}, l_{it}, m_{it}) - \beta_0 - \beta_n \ln(n_{it}) - \beta_k \ln(k_{it}), \tag{8}$$

which is conditioned on parameter values β_l, β_k, and β_0. Combining this with the assumed productivity process results in the moment condition

$$\begin{aligned} E[\epsilon_{it} + \vartheta_{it}|I_{it}] = E[&\ln(y_{it}) - \beta_0 - \beta_n \ln(n_{it}) - \beta_k \ln(k_{it}) - \rho\hat{z}_{it-1}(\beta_l, \beta_k, \beta_0) \\ &- \beta_z \hat{h}^+_{it}(\hat{z}_{it-1}(\beta_l, \beta_k, \beta_0), \hat{\mathbf{z}}_{t-1}(\beta_l, \beta_k, \beta_0))|I_{it}] = 0. \end{aligned} \tag{9}$$

The key distinction from the standard control function approach is the quantity $\hat{h}^+_{it}$ and its marginal effect β_z. In the estimation, the quantity can be calculated based on the productivity estimates of the lagged period. More formally, it is straightforward to note that the $\hat{z}_{it-1}(\beta_l, \beta_k, \beta_0)$ can be used to construct $\hat{\mathbf{z}}_{t-1}(\beta_l, \beta_k, \beta_0)$, and consequently, $\hat{h}^+_{it}(\hat{z}_{it-1}(\beta_l, \beta_k, \beta_0), \hat{\mathbf{z}}_{t-1}(\beta_l, \beta_k, \beta_0))$. To calculate this, information about worker flows across establishments is required. Additionally, I need to assume that the establishment's productivity vector, which determines the quality of the employees they hire, is included in the information set. This assumption is consistent with the later-specified model and is no more restrictive than the information assumptions made in models where distributions are treated as state variables. Furthermore, it is necessary to expand the set of instruments to include a suitable variable from the information set of the establishments.

Using a set of instruments from the information set and applying standard GMM estimation methods, the parameters can be estimated. In practice, I use a third-order polynomial to model the control function and the productivity process. Following the approach of De Loecker & Warzynski (2012), I incorporate time dummies when estimating the control function in the first step. Additionally, to significantly reduce computing time, I center the productivity process-related parameters, as described in the appendix of ACF.[8]

The primary objective of employing the estimation method described above is to address the challenges posed by simultaneity and selection. As previously defined, the coefficient β_z represents the additional productivity gain obtained from hiring, which producers consider when calculating expectations during the hiring process. Consequently, this method is robust against hiring incentives that arise from both the pursuit of spillover effects and traditional channels. By alleviating some of the endogeneity concerns associated with using fixed-effects models to estimate spillovers, the proposed method offers a more accurate understanding of the potential impacts of hiring individuals from more productive establishments at the microeconomic level.

2.2 Finnish Employer-employee Data

I use matched employer-employee data from Finnish manufacturing from 1995 to 2012 for the empirical analysis. The dataset contains information on all Finnish individuals and their employers, allowing me to track worker movements and identify employer characteristics. The employer data concerns firms in the manufacturing sector with at least 20 employees, including establishments even with fewer workers. I exclude government-owned establishments and special legal forms of companies[9]. Additionally, I filter out establishments with fewer than one full-time worker. The filtering leaves me with approximately 230 thousand observations of 32 thousand unique establishments.

I utilize information on the value added, wage bill, materials, employment, and investments from the employer data. However, the investment series has some significant outliers, so I apply winsorization to the investments at the one percent level to retain as much information as possible. Then, using the perpetual inventory method, I construct a series for capital stock with the investment data, which evolves according

[8]The computational complexity arises from the need to recalculate $\hat{h}_{it}$ in each iteration using the mobility-link matrix.

[9]These include legal forms such as those related to the estate of deceased individuals.

to the formula $k_t = (1 - \delta)k_{t-1} + i_t$, where δ represents the depreciation rate, which I set at 0.1, and i_t represents the investments. Finally, I define the initial value of capital stock as $k_0 = \max\{i_t/\delta, 0\}$.

In the estimation, I use the wage compensations to measure labor input. This choice of labor input measure is a conventional approach to correct the effects of different human capital levels in this type of estimation. Similarly, to correct for the impact of human capital heterogeneity and as the interest is on the effects of hiring on establishment productivity, I 'quality correct' the number of hires from better establishments by multiplying the number of hires by their mean wage divided by the average wage in the manufacturing establishments. I analyze the impact of these choices in Appendix B, which contains robustness checks for the main results.

2.3 Results from the Spillover Estimation with Control Function Approach

The results from the augmented control function approach in Table 1 reveal that the estimate for the spillovers is positive and statistically significant. The multiplier directly implies that one hire from a more productive establishment brings a 0.65 percent increase in productivity on average. However, the inability to account for price and distributional changes limits our understanding of the aggregate implications of the results. Nonetheless, utilizing the available data, I can perform a back-of-the-envelope calculation by multiplying the spillover estimate with an approximate mean number of hires from the more productive establishments. This calculation yields an average productivity impact of 0.27 percentage points.[10]

For comparison, I report estimated production function parameters using the fixed-effects OLS approach and the standard ACF method. The estimates for labor input elasticity are similar across all specifications,

[10] As I cannot observe the sending establishment for all hires, I calculate the back-of-envelope figure by dividing the average number of hires from more productive establishments by the share of observable senders, then multiplying it by the regression multiplier. This approach has several limitations as it assumes that all hires are job-to-job transitions from one establishment to another. However, it provides a rough estimate of the potential aggregate impact.

Table 1: Input elasticity estimates and the spillover estimate with extended control function approach.

	Estimation Method:		
	FE-OLS	ACF	ACF-SO
β_l	0.594	0.599	0.599
	[0.582; 0.606]	[0.580;0.617]	[0.623;0.664]
β_k	0.103	0.257	0.253
	[0.097; 0.109]	[0.243;0.274]	[0.239;0.267]
β_z			0.0065
			[0.0031; 0.0169]

Notes: The numbers in the parenthesis represent the bootstrapped confidence intervals at 5%-level. The bootstrapping is executed by randomizing with replacement the same quantity of establishments, as in the original data, in each round and then repeating the estimation 200 times. In the randomization process, I keep the mobility links intact and recalculate the productivity estimate for the 'sending' establishments that do not end up in the sample based on the current parameter values. The goal is to avoid potential problems arising from the fact that some well-linked establishment does not end up in the bootstrapped sample. The period covered in the analysis is from 1995 to 2012. The instruments used in the estimation include l_t and k_t. Note that other instruments are handled when centering out the productivity process in the middle of the estimation. I employ a third-order polynomial to model productivity to ensure reliability and prevent potential overestimation of spillover effects.

ranging from 0.594 to 0.599. However, the ACF method yields a β_k estimate of 0.257, much higher than the fixed effect approach estimate of 0.103. As mentioned in the ACF, low estimates of capital input elasticity are a common feature of the fixed-effects approach, which would be valid if individual productivity remained constant over the years. It is important to highlight that the multipliers in the standard ACF and the ACF with a spillover component differ only slightly.

In Appendix B, I explore the sensitivity of the results to using headcount as a measure of labor. The results are similar with respect to spillovers. However, the elasticity of labor increases and capital decreases when the measure of labor input is altered.[11] The most likely reason for the change is that the headcount does not take properly into account different skill levels. Thus, wage stock is more appropriate for the main result above. Similarly, I explore how making the quality adjustment to hires from more productive firms affects the results. Excluding the quality adjustment with average wages almost doubles the spillover estimate. Therefore, making the quality adjustment is important when exploring the connection between the establishment productivities with a worker acting as a link between the two.

It is worth noting that the earlier spillover estimate does not take a stance on whether the productivity increase arises from individual human capital or from the establishment's productivity, which is common to all workers and increases as new knowledge becomes available. Even if the quality adjustment has already halved the effect, it is important to acknowledge that the spillover estimate provided earlier does not provide a conclusive answer. To inform modeling decisions, I examine the impact of a "knowledgeable" worker leaving immediately, who may have transmitted new information to the establishment. I compare establishments where an immediate separation occurs with those where it does not, and the results reported in Appendix C reveal no statistically significant difference in the evolution of productivity between the two groups. Therefore, it is reasonable for the modeling purposes to assume that productivity improvements resulting from spillovers increase the productivity of all workers rather than being solely embedded in individual workers' human capital.¨

As worker flows from more productive establishments appear to contribute to output growth, the next step is to assess the quantitative significance of this mechanism. To achieve this objective, I develop a general equilibrium model in the following section that respects all the assumptions made in the above estimation.

[11] Qualitatively, the effect of changing the labor input measure to headcount is similar to Lochner & Schulz (2022), who make a more serious attempt to measure quality-adjusted labor input.

3 Model with Knowledge Diffusion through Hiring

To analyze the aggregate significance of knowledge diffusion through hiring, I develop a general equilibrium model that incorporates the diffusion of knowledge through hiring. The model is based on the endogenous growth version of Hopenhayn & Rogerson's (1993) model in Poschke (2009). In addition, I introduce a knowledge diffusion component inspired by the work of Lucas (2009), Perla & Tonetti (2014), and Lucas & Moll (2014). In the model, workers learn about their employer's productivity and can share some of that knowledge when they move to new jobs. The ability of workers to transmit knowledge has important implications for establishments' hiring strategies, as they understand the potential for acquiring new knowledge. These decisions, in turn, have broader implications for aggregate outcomes through the general equilibrium.

3.1 Establishments

Incumbents. Incumbents maximize their expected sum of profits by discounting the future at a rate of $1/(1+r_t)$. They decide on the number of new workers to hire or lay off and whether to continue. The relevant state variables for the incumbent's decisions include productivity, denoted as z_t, and the number of employees at the beginning of the period, denoted as n_{t-1}. Incumbents use decreasing returns to scale technology and labor as the only input, $f(z_t, n_t) = \exp(z_t)n_t^{\alpha}$, where $0 < \alpha < 1$. I exclude capital from consideration as the focus is solely on the employment aspects of the economy.

In each period, establishments pay a fixed operating cost, $f_{f,t}$, and the wage compensations, $w_t n_t$. Moreover, the establishments are subject to convex relative adjustment costs, expressed as $d(h_t, s_t, n_{t-1}) = (f_{a,t}/2)[(h_t + s_t)/\bar{n}]^2\bar{n}$. Compared to the standard adjustment cost function, this specification introduces a minor difference where the adjustment is relative to the average employment between periods, denoted as $\bar{n} = 0.5(n_t + n_{t-1}) = n_{t-1} + 0.5(h_t + s_t)$. The specification allows consistent handling of entrants with zero workers.

When determining the optimal number of workers to hire, incumbents not only influence their current workforce but also impact their expected future productivity. Hiring connects to the productivity dimension because of the probability of attaining spillover changes. The productivity dimension of hiring is a departure from the parsimonious firm dynamics model, which assumes an exogenous productivity process.

The probability of spillover depends on two endogenous factors: the number of hires, denoted as h_t, and the distribution of knowledge among the pool of reallocating workers, represented by $F_t(z)$. Together, these factors determine the likelihood of achieving a fixed amount of spillover denoted as η. Workers from more productive establishments than z_t can transmit this fixed spillover, and attaining even one worker is sufficient for receiving the spillover. Therefore, there is a probability of $1 - F_t(z_t)^{h_t}$ that even one worker comes from a better establishment. To summarize, the endogenous component of the establishments' productivity process can be expressed as:

$$\eta\chi_t, \qquad \text{where} \quad \chi_t \sim \text{Bernoulli}(1 - F_t(z_t)^{h_t}). \tag{10}$$

In this equation, χ_t is a stochastic variable that takes on values of zero or one, indicating whether there is at least one hire from a better establishment that leads to the occurrence of spillover.

In addition to the endogenous component, idiosyncratic shocks impact the establishments' productivity. The shocks, denoted as u_t, are drawn from a normal distribution with mean zero and variance σ_u^2. The shocks, spillovers, and current productivity collectively determine the next period's productivity

$$z_{t+1} = z_t + \eta\chi_t + u_t, \qquad u_t \sim \text{N}(0, \sigma_u^2). \tag{11}$$

One noteworthy feature of the productivity process is that it exhibits a random walk without the spillover component. The random walk aspect is central to the mechanism that generates the residual growth, along with endogenous exit and entrant imitation, that cannot be attributed to the knowledge diffusion through hiring.

By integrating all the elements, we can formulate the value function for incumbents as follows:

$$V(z_t, n_{t-1}) = \max_{h_t, s_t} \Bigg\{ \pi(z_t, n_{t-1}) + \frac{1}{1+r_t} \max\{\mathrm{E}_{t|h_t, z_t}[V(z_{t+1}, n_t)], \tag{12}$$

$$- c(0, n_{t-1}, n_{t-1})\} \Bigg\} \tag{13}$$

$$\text{s.t.} \quad \pi(z_t, n_{t-1}) = \exp(z_t) n_{t-1}^{\alpha} - w_t n_{t-1} - w_t d(h_t, s_t, n_{t-1}) - w_t f_{f,t} \tag{14}$$

$$n_t = n_{t-1} + h_t - s_t, \tag{15}$$

This optimization problem is subject to knowledge distribution and prices. The solution to the incumbent's problem consists of three policy functions: $h(z_t, n_{t-1})$, $s(z_t, n_{t-1})$, and $y(z_t, n_{t-1})$. These functions describe the employment choices and continuation decisions made by incumbents.

From the standpoint of an incumbent firm, the diffusion of knowledge through hiring has several implications for their decision-making. Firstly, when hiring is added as a part of the establishment's expected productivity, the optimal size of the establishment can change. In some cases, hiring additional workers may be beneficial to enhance the likelihood of experiencing spillover effects. This mechanism also means that scaling up can occur gradually, with positive hiring over several periods. However, it is important to note that the presence of technology with decreasing returns to scale limits the establishment's ability to expand its size infinitely. These behavioral changes emerge from the knowledge diffusion mechanism, distinguishing this model from a canonical firm/establishment dynamics model.

It's worth noting that hiring and separation must be handled separately instead of implementing a common employment adjustment policy. This is because spillover effects may make it appealing to rotate workers, even if keeping the establishment's size unchanged is optimal. However, the convex adjustment costs ensure that changing all workers every period is not feasible.

Entrants. The economy features an infinite supply of potential entrants who can imitate the average productivity of incumbents as they assess the profitability of entering the market. The entrants compare the expected value of entering the market to the entry costs, $f_{e,t}$. Therefore, we can express the condition for free entry as follows:

$$w_t f_{e,t} \leq \int V(z_t, 0) G_t(dz), \qquad G_t \sim \mathrm{N}(a_{e,t}, \sigma_z^2). \tag{16}$$

When entrants decide to enter the market, they draw productivity from the distribution G. The distribution is a normal distribution with a fixed variance σ_z^2 and a mean, $a_{e,t}$, which tracks the incumbents' mean productivity from a distance κ. The tracking of mean productivity by entrants represents the imitation process and serves as a key component of the growth mechanism, as it sustains overall economic growth. Further discussion on this feature is provided in subsection 3.5. Additionally, the initial draws generate some knowledge, which spreads via the knowledge diffusion mechanism.

3.2 Household

The economy's infinitely-lived household aims to maximize the lifetime utility through consumption and labor supply decisions. The lifetime utility consists of periodically separable utility functions $u(c_t, l_t) = \theta \ln(c_t) - l_t$, where θ represents 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 given by $s_{t+1} + c_t = (1 + r_t)s_t + w_t l_t$. In the budget constraint, the s is the value of shares owned by households, as they own all the shares of the active and entering establishments. The shares yield a periodic return of $r_t s_t$ and possess a value s_t. The periodic returns are equal to the profits generated by establishments in the equilibrium. By solving the households' maximization problem, I obtain an intra-temporal optimality condition $c_t = w_t\theta$ and standard Euler equation $(c_{t+1}/c_t) = \beta(1 + r_{t+1})$, where $1 + r_t = (1 + g)/\beta$. The relationship between rates, growth, and the discount rate is used to discount future profits along the growth path.

3.3 Aggregates and Market Clearing Conditions

Establishment Distribution. It is necessary to solve the distribution of establishments so that I can calculate aggregate variables such as output. 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 policies. As a distinction from, for example, Hopenhayn & Rogerson's (1993) model, the optimal employment policy also affects transition probabilities on the productivity dimension. By combining the transition matrix with the entry and exit decisions of establishments, I can specify the law of motion for the establishment distribution, $\mu_t(\mathbf{x}_t)$, as

$$\mu_{t+1}(\mathbf{x}_{t+1}) = \int (1 - y_t(\mathbf{x}_t))Q_t(\mathbf{x}_{t+1}|\mathbf{x}_t, n_t(\mathbf{x}_t))[\mu_t(d\mathbf{x}_t) \\ + m_t\mathbb{I}(n_t = 0)G_t(dz_t)], \tag{17}$$

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, and it can be defined as:

$$a_{i,t} = \int z \left(\int \mu_t(d\mathbf{x}_t) \right)^{-1} \mu_t(d\mathbf{x}_t). \tag{18}$$

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

Workers' Knowledge Distribution. The core part of the knowledge diffusion mechanism is the knowledge distribution of reallocating workers. For simplicity, each reallocating worker remembers their former employer's productivity level. Consequently, the knowledge distribution $F_t(z)$ is constructed by weighting the establishment distribution according to the number of workers reallocating from each productivity level.

As mentioned previously, knowledge distribution plays a crucial role in shaping the choices of individual establishments through general equilibrium. The feedback link makes the Markov chain that describes the evolution of incumbent establishments' productivities interactive in productivity dimension as changes in distribution impact the behavior of establishments, and their behavior further shapes the distribution.[12]

Labor Market Clearing. Households determine the labor supply and establishments' labor demand; these two must coincide in the equilibrium. To recover the household's labor supply, I impose the condition of asset market clearing, which states that $s_{t+1} = s_t = \int V(z_t, n_{t-1})\mu_t(d\mathbf{x}_t)$ in each period. It implies that the household's supply of labor is $l_t = \theta - \pi_t/w_t$, where π is the aggregate profit. The supply must equal the demand set by the establishments. By utilizing the establishment measure $\mu(\mathbf{x})$, establishment demand for labor is

$$\bar{n}_t = \int n_t(\mathbf{x}_t)\mu_t(d\mathbf{x}_t) + f_{f,t}\int \mu_t(d\mathbf{x}_t) + \int d(n_t(\mathbf{x}_t), n_{t-1})\mu(d\mathbf{x}_t) + f_{e,t}m_t. \tag{19}$$

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

$$\bar{\pi}_t = \int \pi(z_t, n_t(\mathbf{x}_t), n_{t-1})\mu_t(d\mathbf{x}_t) - w_t f_{e,t}m_t - w_t \int y(\mathbf{x}_t)d(0, s_t, n_{t-1})\mu(d\mathbf{x}_t). \tag{20}$$

Now 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 have normalized the price of the consumption good to unity, consists of sequences of (1) optimal policies, $\{h_t(z_t, n_{t-1}),\ s_t(z_t, n_{t-1}),\ y_t(z_t, n_{t-1})\}_{t=0}^{\infty}$, of the incumbent establishment (2) wages $\{w_t\}_{t=0}^{\infty}$, (3) establishment distributions $\{\mu_t(z_t, n_{t-1})\}_{t=0}^{\infty}$, and (4) the masses of entrants $\{m_t\}_{t=0}^{\infty}$. These elements satisfy the following conditions: optimal policies solve the incumbent establishment's problem, wages are such that the free entry condition is

[12] See, for example, Köning et al. (2016) for a theory of innovation and imitation with interactive Markov chain.

met, distribution follows its law of motion, and the labor market clears.

In the subsequent analysis, I will solely focus on the balanced growth equilibrium.[13] The balanced growth equilibrium represents a competitive equilibrium in which aggregate productivity, consumption and output, and wages constantly grow at the rate of g. Additionally, the establishment productivity distribution's shape will remain invariant. However, in logs, it will scale up in steps of g every period.

I stationarize the balanced growth equilibrium by transforming growing variables according to $\hat{b}_t = b_t e^{-gt} = b$ and constant variables according to $\hat{k}_t = k_t = k$. This transformation implies that the establishment productivity process will acquire a negative drift equal to g. The 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 Discussion of the Aggregate Growth Mechanism and Model Assumptions

As the focus is on understanding the aggregate growth consequences of knowledge diffusion, I describe the operation of the growth mechanism in detail. Knowledge diffusion through hiring plays a significant role in determining the rate of economic growth. The mechanism leads to an increase in average productivity as some establishments gain knowledge spillover in each period. However, the probability of the increase depends on the type of worker reallocation in the economy through the equilibrium.

In addition to knowledge diffusion across incumbents, aggregate growth results from establishment selection and idiosyncratic shocks. Since the productivity process does not revert to its mean, the variance of the establishment productivity distribution increases each period. As a result, some establishments are driven to the exit threshold, which truncates the productivity distribution from the left. The truncation and the increase in variance imply an increase in average productivity.

Entrants sustain aggregate growth by imitating the productivity

[13] More detailed discussion about this type of equilibrium can be found in Poschke (2009).

increases generated by the knowledge diffusion mechanism, idiosyncratic shocks, and selection. Without the imitation mechanism, the productivity distribution of establishments would thin out over time, which makes imitation an essential part of the growth mechanism.

The main theoretical contribution of this study lies in enhancing a conventional model of firm dynamics by incorporating a spillover component that the available data can directly inform. This allows for a more accurate evaluation of the effects of the diffusion, as it is not the residual of other growth mechanisms. However, it is important to note that I have overlooked the intricate interplay between wage heterogeneity and knowledge spillovers to improve tractability.

Studying the combination of spillovers and wage heterogeneity is an intriguing avenue of research. For instance, the spillovers could be introduced into an on-the-job search framework based on Postel-Vinay & Robin (2002). Nevertheless, models falling under this category primarily emphasize the employer side of the economy, devoting less attention to some of the central aspects of firm dynamics, such as aggregate growth, multi-worker firms, or endogenous entry and exit. To comprehensively address all these factors simultaneously, I have shifted the model's focus entirely to the producer side to provide an alternative angle.

4 Quantitative Results

In this section, I assess the quantitative significance of the knowledge diffusion mechanism. I calibrate the model by utilizing the estimates from the empirical section and central moments of establishment dynamics. Based on the calibrated model, knowledge diffusion through hiring increases aggregate productivity growth by 0.35 percentage points. Moreover, knowledge diffusion increases the output by 4.3 percent. As a policy experiment, I study the interaction of knowledge diffusion and firing costs. Results imply that the adverse effects of firing costs increase by a factor of 1.8.

4.1 Model Calibration

I calibrate the parameters to fit the model to the same data as in the empirical section. The goal is to utilize the empirical section as much as possible in fixing the parameter values. The remaining parameters that cannot directly be attached with external evidence, I calibrate internally to match central moments of the establishment dynamics.

Variable	Value	Explanation	Target	Model
External				
θ	1.0	Normalization		
β	0.95	Convention		
α	0.64	ACF estimation		
σ_z	0.60	Std. of entrant prod.		
σ_u	0.17	Std. of prod. diff.		
ψ	0.18	Knowledge mob. adj.		
Internal				
η	0.016	Infered from ACF estimate	0.0065	0.0065
f_e	4.1	Infered from mean size	16	16
f_f	0.049	Infered from entry rate	0.038	0.037
f_a	1.5	Infered from job turnover	0.14	0.13
κ	0.50	Infered from growth rate	0.026	0.026

Table 2: Model calibration and data fit

First, I set the discount rate and the utility function parameter. 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 of aggregate variables rather than absolute levels.

Second, the estimation gives direct values for the output elasticity of labor, the standard deviation of entrant productivities, and productivity shocks. I use 0.60 from the spillover augmented control function estimation as the output elasticity of labor. This approximately corresponds to the average labor share of the Finnish economy. Moreover, the control function approach gives an estimate of the productivity level, and I use this information directly in the calibration. To fix the standard deviation of entrants' productivities, I calculate the dispersion of productivities for establishments in ages 0-2, and the corresponding value is 0.43. The law of motion for productivity directly gives a way to back out the variance of productivity shocks net of the spillovers. I use these values and set the standard deviation of productivity innovation to 0.18. Moreover, to ensure no additional variation in these standard deviation figures, I remove yearly and 5-digit industry fixed effects from them.

Third, a limitation of the empirical part is that some of the hires come from elsewhere than other manufacturing establishments, and in the model, mobility comes only from other establishments. To avoid biased conclusions, I must apply a correction to this. Therefore, I introduce an additional parameter ψ, which tells how many reallocating workers remember the previous employers' productivity and, thus, represent the within-manufacturing sector reallocation. I fix the value of this knowledge mobility adjustment parameter based on the ratio of observed manufacturing establishment transitions compared to all hires; the value is 0.18.

Fourth, I use five parameters to target five data moments. The remaining parameters are the spillover size, entry costs, fixed costs, adjustment costs, and the imitation distance parameter. As the model features decreasing returns from spillovers through hiring, the estimate itself cannot be used directly as it only gives the average spillover per hire. Therefore, I calculate the corresponding regression multiplier of average spillover per hire from the model and use spillover parameter η to match that to the estimate. The rest of the calibration is relatively standard; mean size and entry rate are used to find proper entry and fixed costs values. The job turnover, calculated as the sum of job creation and destruction over the total number of jobs, helps to pin down the adjustment cost parameter. Finally, the average aggregate growth rate between 1995 and 2012 is used to pin down the value for the imitation distance parameter. Naturally, these arguments are heuristic as the moment matching determines all parameters jointly.

Table 2 displays calibrated parameter values and the empirical fit of the model. From the table, we can observe that entering the manufacturing sector costs the equivalent of a wage paid for 4.1 years to a single worker. Running the establishment entails the cost of a wage paid for approximately 0.6 months to a single worker. The adjustment cost parameters tell us that rotating a single worker in a mean-sized establishment costs around 2.25 months' wage. Overall the empirical fit is good, and the most important characteristics, namely the aggregate growth and the spillover coefficient, give close to an exact match.

4.2 Quantitative Significance of Knowledge Diffused by Workers

	Calibrated (BM), $\eta = 0.016$	No spillovers, $\eta = 0$
Output / Wage	100	95.7
Growth (%)	2.56	2.21
Entry rate (%)	3.70	3.14
Turnover (%)	13.3	14.2
Mean Size	16.1	7.20
Equivalent Variation	100	108

Table 3: The aggregate impact of spillovers.

To explore the quantitative significance of knowledge diffusion, I conduct a simple counterfactual experiment by shutting down the spillover channel. To do this, I set η to zero and solve for the balanced growth equilibrium of the model while keeping other parameters fixed. Although this consideration is more theoretical, it mimics a situation where strong enough non-competition clauses could be implemented to shut down any flow of information through workers across establishments.

The main results, reported in Table 3, reveal that knowledge diffusion through hiring has a quantitatively significant impact. Two key observations support the conclusion. First, shutting down the knowledge diffused by workers decreases the aggregate growth rate by 0.35 percentage points. Second, the level of output reduces significantly by 4.3 percent. To summarize the total effect of both changes, I calculate the equivalent variation between the economies. From the household's problem, it is straightforward to determine how much consumption should be increased in the spillover-less economy to achieve the benchmark economy's utility level. The results show that consumption had to be increased by 8 percent to compensate for the lack of productivity increases from the spillovers.

In addition to the growth and welfare effects, the spillover mechanism also significantly impacts the central parts of establishment dynamics. Although the effect is small, the spillover channel decreases the establishment's job turnover, mainly due to the increase in the denominator. The mechanism also increases exit and entry, making the environment more dynamic. However, the mechanism also significantly increases the mean size of establishments, despite their shortened expected lifetime. This increase is a natural consequence of the spillover mechanism, as it favors small establishments that can benefit from the knowledge of nearly every worker. The unequal benefits across establishment distribution can also be seen from the whole distribution, which widens and moves to the right. The changes in the size distribution indicate that spillovers let some establishments escape the exit threshold with significant leaps, which would not be possible without the spillover mechanism.

The findings indicate that in a relatively undynamic environment like the Finnish manufacturing sector, a significant portion of the growth comes from worker-transmitted knowledge. These results suggest further investigating the impact of worker-based knowledge diffusion. While my analysis has focused on the positive aspects of knowledge diffusion, the following section takes a normative approach to explore how hiring-based knowledge diffusion affects the impact of firing costs. The effect of employment protection legislation, represented by firing costs, has been extensively studied in the literature. Therefore, it's intriguing to see how knowledge diffusion alters the effects of this policy.

4.3 Firing Costs and Knowledge Spillovers

I consider the role of firing costs to see how knowledge diffusion through hiring affects economic policy. Based on the previous literature, the firing costs severely impact 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 also impairs knowledge diffusion.

I conduct a counterfactual exercise similar to the previous section to

	With spillovers, $\eta = 0.016$		Without spillovers, $\eta = 0$	
	BM, $\lambda = 0$	FC, $\lambda = 1$	BM, $\lambda = 0$	FC, $\lambda = 1$
Output / Wage	100	96.4	100	96.8
Growth (%)	2.56	2.39	2.56	2.55
Entry rate (%)	3.70	3.32	4.03	3.98
Turnover (%)	13.3	10.3	14.0	9.01
Mean Size	16.1	13.3	16.1	16.8
Equivalent Variation	100	109	100	105

Table 4: The aggregate impact of firing costs.

understand how knowledge diffusion changes the effects of firing costs. To the model, I add a firing cost function $d_f(s_t) = \lambda s_t$ also paid in labor and set the value λ to one as in Poschke (2009). Moreover, as the idea is to understand the potential bias in conclusions derived from a model without the spillover mechanism, I re-calibrate the model and exclude the spillover target. Appendix D contains the parameter values for the re-calibrated model. In the re-calibrated model, I repeat the same exercise of increasing the firing costs to one. Comparing the results between these two firing cost increases helps us understand spillovers' role in the consequences of these economic policies.

Firing costs impact the central descriptives of the calibrated economy based on the results reported in Table 4. According to the results, the firing costs decrease the aggregate growth by 0.17 percentage points and the output level by 3.6 percent. Moreover, the equivalent variation between the economies is a 9 percent increase in consumption to compensate for the negative impact of firing costs. Introducing the firing costs also impacts the business dynamism as the turnover decreases by three percentage points, mean size decreases by 2.8 workers, and entry decreases by 0.38 percentage points.

In the hypothetical economy without knowledge spillovers, the firing costs cause smaller changes as in the calibrated economy. According to the results in Table 4, firing costs have almost no effect on aggregate growth. However, the firing cost decreases output by 3.2 percent, and the equivalent variation amounts to 5 percent of consumption. The effect on the business dynamism is similar to before the turnover decreases by five percentage points, the mean size increases by 0.7 workers, and exit stays virtually intact. By comparing the effect of firing costs between the two alternative specifications, we can see that knowledge diffusion through hiring makes the adverse effects 1.8 times as large.

The size of the growth effect aligns with the values found in the literature. Even if there is no 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 similar firing costs reduce the growth by 0.09 percentage points, and Mukoyama & Osotimehin (2019) find a 0.1–0.2 percentage point effect of firing costs depending on the calibration. Compared to both studies, the effect I find is within a reasonable range. Notice also that in my model, the adjustment costs already affect the labor adjustments, and the firing cost comes on top of that and introduces the inaction region to the establishments' labor adjustment policies.

5 Conclusion

I find empirical evidence that shows a link between hiring from more productive establishments and the productivity growth of establishments. Motivated by the evidence, I examine the quantitative significance of knowledge diffusion through hiring in a standard firm dynamics framework. I demonstrate that the knowledge diffusion mechanism significantly impacts aggregate growth and establishment dynamics by calibrating the framework to central data moments. Furthermore, I show that the mechanism exacerbates the adverse effects of firing costs.

From a policy perspective, the study shows that firing costs can have a more detrimental impact on aggregate outcomes than previously thought. In addition to hindering reallocation, firing costs reduce the rate of knowledge diffusion. Considering this mechanism reveals that the adverse effect of firing costs can be 1.8 times greater. While the analysis does not explicitly examine the impact of non-compete contracts, it suggests the potential upper limit of their effect if they were to obstruct knowledge flow through worker mobility completely. A more comprehensive analysis of the impact of such contracts on aggregate growth would be an intriguing avenue for future research, which would need to consider the incentives that intellectual property protection creates for innovation.

Throughout my paper, I focus on the establishment dynamics aspect of knowledge diffusion through hiring, providing less detail on modeling the labor market. A more thorough model of the labor market could offer additional insight into the effects of knowledge diffusion on aggregate growth and business dynamics. Additionally, studying the relationship between hiring and producers' productivity growth across a more extensive range of countries could deepen our understanding, as the current evidence is mainly from Nordic countries.

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Appendix

Appendix A. Assumptions of the ACF Approach

For convenience, I list below the basic assumptions of the control function approach in ACF:

A1 – Information set: The firm's information set, I_{it}, includes productivity shocks $\{z_{i\tau}\}_{\tau=0}^{t}$. The transitory shocks ϵ_{it} satisfy $E[\epsilon_{it}|I_{it}] = 0$.

A2 – First Order Markov: Productivity shocks evolve according to the distribution $p(z_{it+1}|I_{it}) = p(z_{it+1}|z_{it})$ and the distribution is known to firms and is stochastically increasing in z_{it}.

A3 – Timing: Firms accumulate capital and labor according to functions $k_{it} = \kappa(k_{it-1}, i_{it-1})$ and $l_{it} = \iota(l_{it-1}, h_{it-1})$, where investment i_{it-1} and hiring h_{it-1} is chosen in period $t-1$.[14]

A4 – Scalar Unobservable: Firms intermediate input demand is given by $m_{it} = f_t(k_{it}, l_{it}, z_{it})$.

A5 – Strict Monotonicity: $f_t(k_{it}, l_{it}, z_{it})$ is strictly increasing in z_{it}.

Appendix B. Additional Spillover Estimations

To assess the robustness of the primary finding, I estimate using an alternative measure of labor input, namely, the number of employees. The results, as presented in Table 5 (columns 1-3), indicate that the spillover estimate remains robust with this alternative measure. However, it is worth noting that the input elasticities have changed as anticipated. Specifically, the input elasticity for labor has increased to 0.885-0.948, whereas the elasticity for capital is valued at 0.134-0.137. This change may be attributed to the potential heterogeneities related to labor input, which the analysis does not account for. Moreover, the results align with Lochner and Schulz's (2022) findings; they also observed a similar increase

[14]This assumption is slightly stricter than the original one. However, it will be consistent with the quantitative model later.

Table 5: Input elasticity estimates and spillover estimates with different specifications.

	Estimation Method:			
	FE-OLS	ACF	ACF-SO	ACF-SO (No Qual. Adj.)
β_l	0.881	0.938	0.917	0.597
	[0.870; 0.894]	[0.926;0.950]	[0.904;0.929]	[0.580;0.615]
β_k	0.093	0.146	0.147	0.252
	[0.087; 0.099]	[0.139;0.154]	[0.139;0.158]	[0.239;0.266]
β_z			0.0074	0.0119
			[0.0024; 0.0137]	[0.0071;0.0218]

Notes: See notes of Table 1.

when they changed their preferred labor input measure to the number of employees.

Table 5 also contains a robustness check related to the quality adjustment of the new hires. If I exclude the wage-based "quality" correction of the hiring inflow, the spillover estimate doubles from 0.0065 in the text to 0.0119. Therefore, adjusting the hiring inflow is essential to control for human capital-related factors. On the other hand, the input elasticities stay relatively similar without quality control.

Appendix C. Nature of the Spillovers

The estimation does not determine whether the increase in productivity is due to more efficient workers or general knowledge improvement that leads to higher productivity for all workers. For instance, consider an establishment with two workers having individual productivities h_1, h_2 and a joint firm productivity component z. The resulting total productivity is $z(h_1 + h_2)$. Now, if h_1 is replaced by a more productive worker $h_3 > h_1$ the productivity would increase. However, we can find a z^* that would result in a similar increase in productivity if $h_1 = h_3$. Even if I use wage stock to measure labor input, which attempts to control worker productivity, and the average wage correction for the hires, some of these concerns remain.

To disentangle between these two potential stories, I analyze a specific

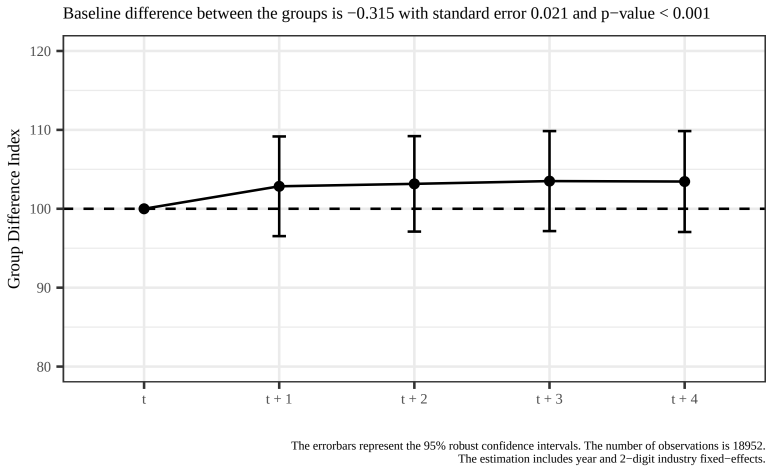

Figure 1: Evolution of productivities in two sets of establishments that hired workers from a better establishment. In the first group are the establishments that lose the worker that came from a better firm, and in the second group are the establishments from which some other worker leaves.

event. I gather all firms that hire at least one worker from a more productive establishment and calculate their productivity estimates $\hat{z}_{it}$. Then, I separate these establishments based on whether some of the hired workers, who potentially transfer knowledge, leave immediately in the next period. If the productivity evolution significantly differs between these two groups, it provides evidence of worker-specific knowledge. If the productivities evolve similarly, the evidence supports the establishment-specific productivity increase. The exercise is descriptive and helpful in guiding modeling choices.

Figure 1 demonstrates the productivity changes when a worker hired from a more productive establishment immediately leaves. The difference between the group where the worker does not immediately leave is not statistically significant. Thus, the evidence in Figure 1 supports the story of establishment-specific productivity increase through spillovers.

To further examine the robustness of the exercise, I consider different alternative specifications for the control group. For example, I relax the assumption that the ”control” group must have some separations immediately in Figure 2. Additionally, based on the first or last applicable

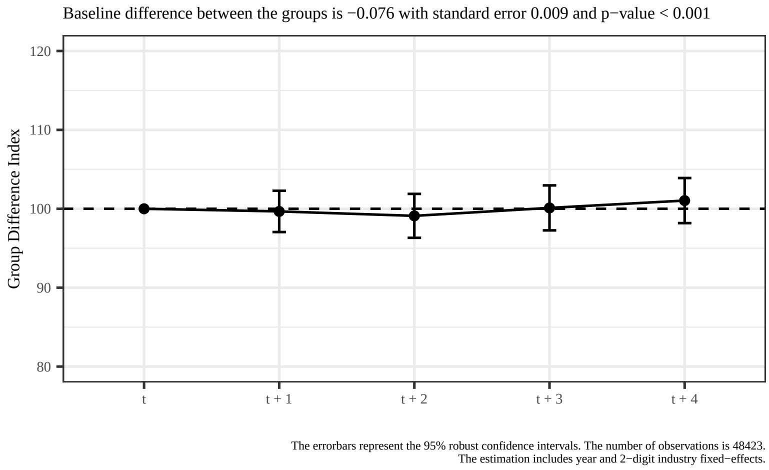

Figure 2: Evolution of productivities in two sets of establishments that hired workers from a better establishment. In the first group are the establishments that lose the worker that arrived from a better firm, and in the second group are the rest of the establishments.

event, I check a specification in which one establishment occurs only once, either in the ”treated” or ”control” group. These results are not reported here. However, this alternative specification does not affect the result.

In light of this exploration, it seems reasonable to study the effect of spillovers on establishment-specific knowledge as I find no evidence that the spillover effect solely stems from productivity increase through workers’ human capital. Therefore, to increase tractability, I ignore the human capital heterogeneity and concentrate on the impact of spillovers on aggregate growth through establishment productivities in the quantitative exercise.

Appendix D. Calibration of the Model without Spillovers

To recalibrate the model without spillovers, I followed the same procedure as in the benchmark model, with the only difference being that I set the spillover to zero and dropped the corresponding target. The results of the calibration are presented in Table 6. Compared to the benchmark case, we

Variable	Value	Explanation	Target	Model
External				
θ	1.0	Normalization		
β	0.95	Convention		
α	0.60	ACF estimation		
σ_z	0.43	Std. of entrant prod.		
σ_u	0.18	Std. of prod. diff.		
ψ	0.0	Knowledge mob. adj.		
Internal				
η	0.0	Infered from ACF estimate	0.0065	0.0
f_e	6.7	Infered from mean size	16	16
f_f	0.20	Infered from entry rate	0.038	0.040
f_a	1.9	Infered from job turnover	0.14	0.14
κ	0.45	Infered from growth rate	0.026	0.026

Table 6: Model re-calibration and data fit.

can observe an increase in the entry cost from 4.1 to 6.7, an increase in fixed costs from 0.049 to 0.20, an increase in adjustment costs from 1.5 to 1.9, and a decrease in the entrants' tracking distance from 0.5 to 0.45.

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