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Firm Productivity Growth and the Knowledge of New Workers

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Abstract

Linked employer-employee data from New Zealand is used to study the relationship between a firm's productivity growth and its exposure to outside knowledge through the hiring of new workers with previous work experience. The estimated relationship between productivity growth and hiring is compared to the predictions implied by two different channels: worker quality and knowledge spillover. Although it is not possible to identify a causal relationship, the productivity of a worker's previous employer is correlated with subsequent productivity growth at the hiring firm. The patterns of this correlation are consistent with both the worker quality and knowledge spillover channels operating simultaneously. Furthermore, if knowledge spillover is occurring, the results suggest the type of knowledge spilling over relates to technological knowledge allowing firms to become more capital intensive, rather than knowledge that improves the efficiency of utilising existing inputs.

JEL CLASSIFICATION D24, J24, J62, O33

KEYWORDS productivity; labour mobility; human capital; knowledge diffusion

Executive Summary

Productivity growth is widely understood to be the key determinant of the long-run prosperity of an economy. By international standards, New Zealand's productivity growth rate has underperformed for a number of decades. In light of this, understanding the drivers of, and barriers to, productivity growth has been a topic of interest to policy makers who look to improve New Zealand's economic performance and international competitiveness.

It has long been speculated in the economic literature that job-to-job transitions could be one of the main channels through which productive ideas developed at one firm can spill over to the wider economy. Indeed, there is some empirical support for this idea. According to the 2019 Business Operation Survey, 59 percent of innovating firms in New Zealand reported that new workers were a source of ideas for innovation. However, the survey data cannot quantify the impact of these new ideas.

This paper uses individual-level data for firms and workers from the Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI) to relate the characteristics of new workers and the productivity level of the workers' previous employer to the subsequent productivity growth experienced by the hiring firm. While it is not possible to draw causal inferences from the model or data, the empirical relationships identified are compared to alternative theories of the mechanisms through which the knowledge of new workers could influence productivity growth in the firm.

Specifically, this paper looks at two channels. The first is the productive knowledge spillover channel in which workers, through their participation in production, learn some of the productivity knowledge used by their employer. This knowledge can be valuable to less productive firms that could apply these more productive ideas to their own production processes. As a result, when workers move from more productive to less productive firms, the less productive hiring firm should improve in productivity (assuming adjustment costs are low enough and workers have enough capacity to absorb knowledge), and this improvement should be large when the productivity difference between the firms is large. Because firms are freely able to discard less productive knowledge, when a worker moves from a less productive to a more productive firm, the more productive hiring firm can disregard the less productive ideas, and there should be no productivity loss.

The second channel is based on the idea the worker's previous firm provides a signal of workers' unmeasured quality. Assessing a worker's quality at a glance is difficult both in the data and in real life. Measures of worker quality are usually derived from wage or education data, but these measures may not accurately predict the value of workers to the firm. However, if more productive firms tend to have higher quality workers, either through a better selection/screening process, or by providing better on-the-job training, then hiring from more productive firms should raise the unmeasured quality of labour in, and hence the productivity of the hiring firm, while hiring from less productive firms should lower it.

Distinguishing between these channels is of interest because the existence of knowledge spillovers implies the potential for aggregate productivity growth through knowledge diffusion. Because knowledge is non-rival, ideas can be infinitely copied and utilized through the whole economy, and the mixing of these ideas in different parts of the economy can generate new ideas, leading to sustained growth. In contrast, the benefits from the reallocation of existing resources (like workers' human capital) are inherently limited. In particular, firm-level productivity improvements due to improving the average worker quality can be sustained only if firms and workers are engaged in training. Transfers of workers between firms may help to improve performance of one firm at the cost to the other, and the impact on aggregate productivity is likely to be small.

The baseline results suggest that the productivity of a new worker's previous employer is strongly correlated with subsequent productivity growth at the hiring firm. In general, hiring from more productive firms is associated with more productivity growth in the hiring firm, and hiring from less productive firms is associated with lower productivity growth.

The results from the analysis are consistent with the predictions from the unobservable worker quality and the productive knowledge spillover channels operating together. When using multi-factor measures of productivity (which control for the use of capital and materials), raising the average productivity level of the less productive firms that new workers are sourced from has the same expected benefit to the hiring firm's productivity growth as raising the average productivity level of the more productive firms workers are hired from. This relationship does not seem to be significantly affected by the various observable worker characteristics looked at in the paper, which is consistent with the idea that the productivity gains relate to some unmeasured component of worker quality.

When firm productivity is measured in terms of labour productivity (value-added per worker), increasing the average productivity level of the firms that workers are sourced from also leads to an expected increase in productivity growth at the hiring firm. However, unlike the multi-factor productivity (MFP) case, raising the average productivity level of the less productive firms that new workers are sourced has a smaller expected benefit to the hiring firm's productivity growth than raising the average productivity level of the more productive firms workers are hired from. This premium associated with hiring workers from more productive firms is consistent with the productive knowledge spillover channel.

Further investigation reveals that this productivity growth premium is related to a similar premia in the capital-labour ratio. This, combined with the result that we do not observe the premium in MFP data, suggests that if the knowledge spillover channel is a driver of labour productivity growth within firms, then the knowledge that spills over is confined to knowledge regarding production technology (how to operate more capital-intensive production methods) rather than pure multi-factor productivity knowledge (how to extract more value from the current production technology).

Extensions to the baseline model provide further support for the idea of a knowledge spillover channel when using labour productivity as the measure of firm's productivity. In these extensions the size of the knowledge spillover premium is larger when hiring from within the same industry (where knowledge is likely to be more applicable to the hiring firm) and when hiring workers with long tenure at both their previous firm and the hiring firm (allowing more time for knowledge to spill over). Such characteristics would be expected to facilitate the spillover of knowledge between firms.

While the particular patterns and relationships seen in this paper cannot be interpreted as causal, the analysis does help to quantify the strength of the relationship between productivity gains and labour mobility. As such, it is useful in identifying which avenues are likely to be the most useful to explore in attempts to understand exactly how new workers benefit hiring firms within the New Zealand economy. One limitation of the analysis is that it excludes very small firms (less than 10 full-time equivalent workers). We would expect labour mobility to have an even greater impact on productivity in these firms, as smaller firms tend to have lower productivity and individual employees have greater potential to influence the performance of the firm as a whole. However, the method used does not allow for the relationship to be robustly estimated for small firms.

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1. Introduction

Improvements in innovation and productivity have long been regarded in the economic literature as the key drive of long-run economic growth. According to New Zealand firms, new staff are an important source of ideas for new innovation. Every two years, Statistics New Zealand surveys businesses about their innovation practices in the Innovation Module of the Business Operations Survey (BOS), a nationally representative survey of firms. In 2019, 42 percent of responding businesses reported that they had implemented some form of innovation in the prior two years.[1] Of those businesses that reported carrying out some form of innovation, 59 percent reported that new staff were an important source of ideas for the innovation that was carried out.

Despite firms reporting that new staff are an important source of ideas for innovation, the mechanism by which this benefit occurs is not well understood. The economic literature has proposed many theoretical channels through which the knowledge of new workers can influence the hiring firm's productivity such as knowledge spillover, work-firm match quality, and worker skill. However, there is scarce empirical support for which, if any, of these channels actually exist in the data.

This paper aims to improve our understanding of the channels through which firms benefit from the knowledge and ideas brought to the firm by new hires. It studies in detail the relationship between characteristics of new hires and measurable productivity growth at the hiring firm. The analysis uses panel data that matches the full population of businesses to their workers to examine how growth in a firm's productivity is related to both the skill/quality of new workers and the knowledge new workers may have acquired working at their previous firms. These empirical relationships are then compared to the predictions made by two theoretical channels that the literature has used to relate firm productivity and labour mobility. Namely, a productive knowledge spillover channel and an unmeasured worker quality channel.

The analysis expands on the previous empirical literature in two key areas. First, due to restrictions in data availability, the previous literature has predominantly focused on examining knowledge spillovers in manufacturing industries, where revenue and cost data are more readily available. The data used in this paper provides coverage of firms in all industries of the measurable economy.[2] Second, another limitation common in the previous literature is only observing employment data at a particular date each year. The employment information available in the New Zealand data is observed at the monthly frequency. Not only does this frequency of observation allow for more precision in the

1 The types of innovation asked about were: (i) product innovation: "did this business introduce onto the market any new or significantly improved goods or services?"; (ii) process innovation: "did this business implement any new or significantly improved operational processes (ie methods of producing or distributing goods or services)?"; (iii) organisational innovation: "did this business implement any new or significantly improved organisational/managerial processes (ie significant changes in this businesses strategies, structures or routines)?"; and (iv) marketing innovation: "did this business implement any new or significantly improved sales or marketing methods which were intended to increase the appeal of goods or services for specific market segments or to gain entry to new markets?"

2 The measured sector of the economy is defined by Statistics New Zealand as industries that mainly contain enterprises that are market producers.

timing of job starts/finishes, but it also ensures that we are able to capture all jobs that a worker undertakes (and not just the jobs where the worker was employed at a particular date each year).

In addition to the empirical contributions, this paper builds upon the theoretical base of the previous literature by adding additional controls to the model that have not generally been used. Previous papers have tended to only control for the hiring intensity of workers from sources for which it is possible to measure productivity (e.g. only hires from other manufacturing firms). A firm's decision to hire workers from sources within the scope of productivity analysis is likely to be correlated with its decision to hire from sources outside that scope. Without controlling for this effect, the estimated size of the productive knowledge spillover effect may be biased. Due to the richness of the New Zealand data, it is possible to introduce controls for hires outside of the scope of our analysis (such as hires from non-market firms, or new entrants to the labour market) as an attempt to control for the possibility of knowledge spillovers from these other sources.

To help distinguish between worker quality and knowledge spillover effects, the analysis makes a distinction between the intensive margin of hiring, proxied by the productivity of the new worker's previous firm, and the extensive margin of hiring, how many workers were hired. Overall, the results from the regressions show that when a firm hires new workers, the productivity of the workers' previous employer is significantly correlated with the productivity gains at the hiring firm following the new hires, even after controlling for changes in the (measured) quality of the firm's labour force.

When firm productivity is measured in terms of multi-factor productivity, higher productivity growth in the hiring firm is positively correlated with a higher than average productivity level of the private-for-profit firms that new workers are sourced from. The size of the expected increase in productivity growth is the same irrespective of whether the firm increases the average productivity of the less productive firms it hires from or increases the average productivity of the more productive firms it hires from. However, when firm-level productivity is measured in terms of labour productivity (value-added per worker), raising the average productivity of the more productive firms that workers are hired from is associated with a larger expected productivity gain at the hiring firm than raising the average productivity of the less productive firms that workers are hired from. In addition, when the flow of new workers into the hiring firm is further sub-divided based on worker and firm characteristics, the variation in productivity gains and losses from these various sub-divisions is larger when using value-added as the productivity measure than when using multi-factor productivity.

The overall pattern of correlations described above does not point to a unique channel through which firms benefit from new workers. Instead, the results are consistent with a story in which new workers affect productivity in the hiring firm through both knowledge spillovers and changing the unmeasured worker quality within the firm. The results also suggest that if productive knowledge spillover is one of the causal drivers of the firm's productivity growth, then the type of knowledge that spills over between firms relates to technology knowledge, which allows firms to take advantage of more capital-intensive production techniques, rather than multi-factor productivity knowledge which would allow for the more efficient utilisation of existing inputs. While it is not possible to definitively conclude the direction of causality in these relationships, these findings do appear to be robust to the attempts we can make to control for causality, suggesting that at least some part of the relationship between the knowledge of new workers and the subsequent productivity growth at the hiring firm is likely to run in the direction from workers to firm productivity.

The remainder of the paper is structured as follows. Section 2 discusses how this paper fits into the existing literature. Section 3 discusses the model used for the analysis. Section 4 details the data sources used. Section 5 presents the results of the analysis. Section 6 concludes.

2. Literature Review

Typically in the empirical literature, the measure of a firm's exposure to new productive knowledge from workers is proxied by the share of new workers at the hiring firm. Using Danish data on several industries, Parrotta and Pozzoli (2012) find that the number of hires of new highly-educated workers — who are likely to be carriers of knowledge between firms — is correlated with productivity growth in the hiring firm. Similarly, Serafinelli (2019) shows that the productivity of Italian manufacturing firms improves when hiring workers from high wage premium firms (a proxy for high productivity firms).[3]

The analytical approach taken in this paper most closely relates to that used by Stoyanov and Zubanov (2012) who use the notion of a 'productivity gap' — the difference between the hiring firm's productivity and the productivity of the new workers' previous employers — as a measure of the hiring firm's exposure to new knowledge. Their analysis shows that for Danish manufacturing firms, hiring new workers from more productive firms benefits the hiring firm's productivity, while hiring new workers from less productive firms does not have a significant effect on the hiring firm's productivity. These correlations match the predictions of the knowledge spillover channel.

Empirically, the analysis in this paper extends that of Stoyanov and Zubanov (2012) by using data that covers all private-for-profit businesses within the measured sector.[4] In addition, the employment data used is able to capture all job spells, not just those observed at a particular date each year. Theoretically, the model used in this paper builds on that of Stoyanov and Zubanov (2012) by including controls for hires from various sources outside the scope of the productivity analysis, and relates the productivity gap to growth in the hiring firm's productivity, rather than the level of productivity. We believe such an approach provides a better fit with the way multi-factor productivity is typically computed in the data.

Not all papers in the literature find support for labour mobility being a channel for productive knowledge spillover. Stockinger and Wolf (2019) find that for multiple German industries the number of new workers hired from superior (defined as higher-paying) establishments does not have a significant effect on the hiring establishment's productivity. However, hiring more workers from lower-paying establishments is associated with productivity gain. Their findings suggest the productivity gains associated with new hires are more consistent with an assortative matching process — where higher (lower) skilled workers move up (down) the firm productivity ladder over time.

Motivated by this finding, we expand the scope of our analysis to also consider other possible channels beyond knowledge spillover through which new workers will benefit the hiring firm. The empirical correlations are then compared to these various channels as a way to help choose between the competing stories for how firms benefit from the knowledge of new workers in New Zealand.

3 Others, like Castillo et al. (2016) have focused on evaluating spillovers from specific government programs designed to support technological development.

4 The measured sector is defined by Statistics New Zealand as "industries that mainly contain enterprises that are market producers. This means they sell their products for economically significant prices that affect the quantity that consumers are willing to purchase".

In the context of the New Zealand literature, the relationship between firm-level innovation and the characteristics of new workers has primarily focused on flows of migrants. McLeod, Fabling, and Maré (2014) find that a higher proportion of recent migrants within the firms' workforce is correlated with a higher probability of self-reporting innovation in the BOS. Sin et al. (2014) find that hiring high-skilled foreigners raises the probability that a firm will self-report both exporting and innovation. While these findings only represent correlations, they are consistent with the causal story of foreign knowledge spillover through the international migration of labour.

The analysis carried out in this paper expands upon this previous New Zealand literature by considering all labour flows, not just those related to international migration. Also, firm-level innovation is viewed through the lens of measurable productivity rather than the binary self-reported BOS responses. This provides an indication of the magnitude of innovation that is occurring within businesses.

3. Model

The analytical framework consists of two stages. The first stage is to derive firm-specific measures of productivity. The second stage is to explicitly model the relationship between growth in the hiring firm's productivity and the firm's exposure to productive knowledge and skills brought to the firm by new workers.

3.1 Measuring productivity

This paper considers a range of alternate measures of firm productivity.[5] The first measure considered is labour productivity, which has the advantages of being straightforward to compute and allowing for direct comparisons on a like-for-like basis between firms in different industries and firms that employ different levels of inputs. Labour productivity is calculated as the real value-added (value of the final output less materials) per full-time equivalent (FTE) worker. More formally, let $A_{i,t}$ denote labour productivity for firm i in year t. Labour productivity is then defined as

$$A_{i,t} = \frac{Y_{i,t} - M_{i,t}}{L_{i,t}}, \tag{1}$$

where $Y_{i,t}$ denotes the real value of the firm's output in year t, $M_{i,t}$ denotes the real value of material inputs into the production process, and $L_{i,t}$ is the measure of labour input in FTE units.

Also considered are various measures of multi-factor productivity (MFP). Multi-factor productivity controls for changes in other factor inputs (such as capital) and returns to scale. However, the measure of MFP is dependent upon the functional form of the benchmark production function that is chosen. Formally, let $Y_{i,j,t}$ denote the output of firm i, in industry j, at time t. The firm's output can be expressed as

$$Y_{i,j,t}(L, K, M) = A_{i,t}F_{j,t}(L, K, M), \tag{2}$$

where $A_{i,t}$ is the firm's MFP, $F_{j,t}(\cdot)$ is the production function technology used by industry j at date t, and L, K, and M, are the firm's choice of labour, capital, and materials respectively.[6] Given information on the firm's level of output, inputs, and a functional form

[5] In addition to firm productivity, some of the analysis examines the capital-labour ratio as a measure of input intensity.

[6] Throughout the rest of this paper, $A_{i,t}$ and the term 'firm productivity' will be used to refer to the firm's productivity measured either as labour productivity or MFP.

for the production function (e.g. Cobb-Douglas technology), (2) can be used to estimate the level of MFP for the firm ($A_{i,t}$) as a residual. One limitation of this approach is that MFP is a relative measure, and like-for-like comparisons can only be made between firms using the same production function benchmark.

3.2 Modeling productivity growth

This paper is primarily focused on how the knowledge of new workers may influence productivity at a hiring firm. The analysis to follow makes a distinction between two types of knowledge. The first type is knowledge that is intrinsic to the structure/operation of a firm such as the managerial, marketing, or production methods employed. Such knowledge is fairly invariant to the specific workers employed by the firm at any point in time. If one worker leaves, a new worker can be hired and placed in the vacant role and the processes used by the firm will be unaffected. What is more, such knowledge is non-rival and can be copied by other firms.

The second type of knowledge is knowledge that is intrinsic to the skill or quality of workers such as education or innate worker ability. This type of knowledge can only be used by the firm when the worker is present. If the worker leaves the firm, they take this type of knowledge will them, thereby lowering productivity at the firm.[7]

Treating the firm's productivity as the Solow residual, the change in the firm's productivity can be related to the change in the knowledge employed by the firm using the relationship

$$\Delta \ln A_{i,j,t} \quad = \quad \Delta I^{\text{firm}}_{i,t} + \gamma \Delta Q_{i,t} + \eta_{i,t}, \tag{3}$$

where $\Delta I^{\text{firm}}_{i,t}$ is the change in the stock of intrinsic knowledge of the firm, $\Delta Q_{i,t}$ is the change in average quality/knowledge of the workers, and $\eta_{i,t}$ is a residual capturing the change in all other productivity factors.

Some component of worker quality/knowledge may be unobservable to the econometrician, and hence unmeasured worker quality could affect $\Delta \ln A_{i,j,t}$ through factors other than $\Delta Q_{i,t}$ if it is orthogonal to observed worker quality. This issue will be discussed later.

By assumption, the stock of intrinsic firm knowledge improves as the firm receives exposure to new productive knowledge brought to the firm by new workers. Therefore we model the change in firm intrinsic knowledge by a proxy for the firms' exposure to new ideas, $\Delta I^{\text{firm}}_{i,t} = \text{Exposure}_{i,t}$ that will be defined and discussed shortly. $\Delta Q_{i,t}$ will fluctuate with the observed quality of the average worker at each firm. The regression analysis also augments (3) with a series of other control variables for factors that may also influence a firm's productivity. The resulting equation that will be used in the regression analysis is given by the following first-difference representation of a dynamic panel model

$$\begin{aligned} \Delta \ln A_{i,j,t} \quad = \quad & \text{Exposure}_{i,t} + \gamma \Delta Q_{i,t} + \delta \Delta \text{ExTurn}_{i,t} + \sum_{l=1}^{L} \alpha_{A,l} \Delta \ln A_{i,j,t-l} \\ & + \theta_{j,t} + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where $\text{ExTurn}_{i,t}$ is a measure of the excess turnover in the firm, $\sum_{l=1}^{L} \beta_{A,l} \Delta \ln A_{i,j,t-l}$ is a series of lagged autoregressive terms, $\theta_{j,t}$ is an industry-year fixed effect, and $\varepsilon_{i,t}$ is the regression residual term.

Excess labour turnover – a measure of the number of worker accessions and separations over and above those required to give effect to the firm's net change in employment – is

[7] The production function generally only controls for the quantity of labour, not the quality.

included as a control because labour turnover can be disruptive to a firm when a significant amount of resources are needed to replace/train workers. Hence high labour turnover may be correlated with low levels of productivity and output.[8]

Lags of past productivity changes are included as the firm's past productivity performance can also affect productivity through influencing the investment and hiring decisions made both today and in the past. Since we are not able to explicitly model all other potential sources of new knowledge, other factors that influence firm productivity are implicitly assumed to be time-invariant (and captured by a firm-specific fixed effect), or random and independent of the other regressors (and captured by the random error term). Finally, the industry-year fixed effect soaks up any industry-wide trends in firm productivity that may remain in the data.

Dynamic panel models are known to suffer from Nickell (1981) bias that creates a correlation between the lagged productivity term and the regression's residual. While first differencing does not directly address the Nickell bias ($\Delta \ln A_{i,j,t-1}$ is still correlated with $\varepsilon_{i,t} = \Delta v_{i,t}$), it does allow us to use $\ln A_{i,t-2}$ as a natural instrument for $\Delta \ln A_{i,j,t-1}$ to control for some of the bias. More sophisticated approaches such as Blundell and Bond (1998) and other adaptations of the Arellano-Bond estimator are also suitable for the estimate of the model described above.

One limitation of the modelling approach adopted here is that it does not allow for the systematic depreciation of productive knowledge at different rates across firms. In reality certain knowledge is likely to become obsolete over time. However, modelling the depreciation of productive knowledge within the firm is challenging and would require many strong assumptions to be made. As a result, we instead rely on the auto-regressive terms and idiosyncratic shocks to proxy for this process.

3.3 Exposure to outside knowledge

The firm's exposure to outside knowledge is assumed to take place through the hiring of new workers with experience at other firms. This is affected by both an intensive margin (the quality of knowledge) and an extensive margin (how many new workers). For reasons that are discussed later, all new productive knowledge is assumed to take one period (a year) to be implemented in the hiring firm before it affects the firm's productivity. Therefore, it is the workers hired in period $t-1$ that affect productivity in period t through the exposure to outside knowledge.

The baseline specification used to model the hiring firm's exposure to outside knowledge is given by

$$\begin{aligned} \text{Exposure}_{i,t} &= \beta_{agg} \frac{\sum_{n \in \mathcal{N}_{i,t-1}} [\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{H_{i,t-1}} \frac{H_{i,t-1}}{L_{i,t-1}} \\ &\quad + \sum_{s \in \mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}. \end{aligned} \tag{5}$$

The first term in the right-hand side is similar to what Stoyanov and Zubanov (2012) refer to as the 'productivity gap'. $\mathcal{N}_{i,t-1}$ represents the set of all new hires by firm i at time $t-1$ from firms for which we are able to measure productivity. With a slight abuse of notation, let new hire n's previous employer also be denoted as firm n.

8 Results do not differ significantly if the share of workers who exit the firm is used in place of excess turnover as a proxy for the disruption of labour turnover.

For each worker n who joins firm i during $t-1$, the date they departed their previous employer is denoted as date $\tau(n) \leq t-1$. The hiring firm's (i's) exposure to new knowledge from worker n depends upon the difference between the productivity between the worker's previous employer at the time they left, $\ln(A_{n,\tau(n)})$, and the hiring firm's productivity at the time worker n joins the firm, $\ln(A_{i,t-1})$.[9]

The new knowledge from each new worker is averaged over all hires with observed productivity gaps and then multiplied by the share of these workers employed by the firm (H/L).

In the data it is not possible to measure the productivity of the previous employer for every new worker. For example, some new hires may be new entrants to the labour market (and hence have no previous employer), or may come from firms for which productivity cannot be measured in the data (e.g. public sector or non-profit firms). As a result, the productivity gap that the econometrician can observe represents only a fraction of the potential exposure to outside knowledge coming from all workers. It is important to control for the entry of workers from these sources because a firm's decisions regarding hiring from firms for which the productivity gap can be computed is likely to be correlated with their decisions to hire new workers from sources for which it cannot. Therefore, failing to control for hires from these other sources would bias our estimate of the marginal effect of new productivity knowledge to the hiring firm, β_{agg}.

Despite not being able to measure the productivity of all firms in the economy, it is possible to identify in the data the reason why the productivity of the worker's previous employer is unavailable. In the second term on the right-hand-side of (5) let $\mathcal{S}_{i,t-1}$ denote the set of sources from which the hiring firm obtains its new workers. $H_{i,s,t-1}/L_{i,t-1}$ represents the number of hires from source $s \in \mathcal{S}_{i,t-1}$ as a fraction of the hiring firm's labour force size (the hiring intensity from source s). This term will be referred to as the hiring intensity. For new hires from sources for which it is not possible to measure the productivity gap, the parameter λ_s represents the average knowledge spillover from source s in terms of the productivity change at the hiring firm.

For hires from sources for which it is possible to measure the productivity gap, the separate productivity gap and hiring intensity terms allow for the distinction between the effects of the intensive (productivity gap) and extensive (hiring intensity) margins of knowledge exposure. In this sense, we expect that on average, the more productive the source firms that a firm is hiring from, the more benefit the hiring firm is likely to receive through the productivity gap. Equation 5 does not rule out the possibility of the hiring firm being exposed to beneficial knowledge from less productive firms. If hiring new workers is in general beneficial to a firm's exposure to knowledge, we will see this effect through the extensive margin, the hiring intensity terms.

All new hires are classified into one of the following sources ($\mathcal{S}$): (i) new workers for whom we have not observed any work history (e.g. new graduates, new immigrants, etc); (ii) hires from firms outside of the scope of productivity analysis (i.e. hires from non-market or not private-for-profit firms); (iii) hires from very small firms for which the measure of productivity is likely to be particularly noisy (defined as less than five full-time equivalent workers); (iv) hires from private-for-profit firms within the scope of analysis but that are missing some of the data required to compute productivity; and (v) hires from private-for-profit firms which are in scope and for which we have the data required to construct productivity

[9] The inclusion of the term $\ln(A_{i,t-1})$ in the measure of exposure to outside knowledge may also generate an indirect source of Nickell bias. However, in the exposure term, the majority of variation is likely to be driven by variation in $A_{n,\tau}$, the productivity of the worker's previous employer, and $H_{i,-1}$, the number of new hires. This should limit the potential bias from $\ln(A_{i,t-1})$.

gap measures. This latter group is the source of the productivity gap measures used to examine the intensive margin of knowledge spillover.

3.3.1 Disaggregated productivity gaps

Not all knowledge is likely to be equally useful to the hiring firm. For example, some knowledge carried by new employees may already be known by the firm, or the firm may have superior knowledge in that area already. In most of the analysis to follow, it will be appropriate to disaggregate the productivity gap into different productivity gaps for sub-groups of hires. This will allow us to estimate differences in the extent of knowledge spillover from each sub-group. For example, rather than use the aggregate productivity gap given in (5), the model for most of the analysis will use separate productivity gaps for hires from *more* and *less* productive firms.

Divide the set of new hires for which we can observe the productivity of the previous employer, $\mathcal{N}_{i,t-1}$, into two mutually exclusive sets $\mathcal{N}^M_{i,t-1}$ and $\mathcal{N}^L_{i,t-1}$ such that

$$\mathcal{N}^M_{i,t-1} \equiv \left\{n \in \mathcal{N}_{i,t-1} : \ln(A_{n,\tau(n)}) - \ln(A_{i,t-1}) \geq 0\right\}, \qquad \text{all } i,t, \tag{6}$$

represents the hires from more productive firms, and

$$\mathcal{N}^L_{i,t-1} \equiv \left\{n \in \mathcal{N}_{i,t-1} : \ln(A_{n,\tau(n)}) - \ln(A_{i,t-1}) < 0\right\}, \qquad \text{all } i,t, \tag{7}$$

represents the hires from less productive firms.

Using these two new subsets, the firm's exposure to knowledge from new hires can be written as

$$\begin{aligned}\text{Exposure}_{i,t} &= \beta_M \frac{\sum_{n\in\mathcal{N}^M_{i,t-1}}[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\ &\quad +\beta_L \frac{\sum_{n\in\mathcal{N}^L_{i,t-1}}[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\ &\quad + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}.\end{aligned} \tag{8}$$

It is important to note that the sum of the productivity differences in the first term of (8) is always positive and the second summation is always negative.

3.3.2 MFP and measuring the productivity gap

As discussed by Fabling and Maré (2015b), it is not possible to directly compare the level of MFP between firms in different industries as MFP is measured relative to the average productivity in the industry. As a result, when hiring workers from another industry, the measures of the productivity gap are potentially biased because they exclude the difference in the average level of productivity between different industries.

Theoretically, no bias will exist when the factors that create differences in productivity across industries cannot be utilised by the hiring firm, but those that gerenate productivity dispersion within industries can be. This might be the case, for example, if the hiring firm is unable to utilize the types of capital or natural resource availability that makes a worker's previous industry more productive on average, but it is able to utilize the superior management practices that made the worker's previous firm highly productive relative to competitors.

The online appendix looks at the potential for this bias to affect the results. The results there indicate that not accounting for the difference in average industry productivity does not appear to have a significant effect on the estimation results.

3.4 Theoretical predictions

The aim of this paper is to investigate how firms benefit from the knowledge of new workers. The empirical analysis to follow will be compared to the predictions made by the hypothesis that labour acts as a channel for *knowledge spillover*. The second hypothesis considered is that a worker's own knowledge contributes via an *unmeasured worker quality* component. These predictions are discussed in more detail below. Table 1 provides a summary of the predictions from each hypothesis for the coefficients in the baseline model described by (8) and (4).

Table 1 — Summary of theoretical predictions

	Parameter predictions for:		
	Productivity gap		Hiring intensity
Channel	β_M	β_L	λ_M & λ_L
Knowledge spillover	> 0	≈ 0	possibly $\lambda > 0$
Unmeasured worker quality	> 0	$\approx \beta_M$	

Note: The parameters in this table relate to the model given by (8) and (4).

3.4.1 Knowledge spillover

It has long been proposed in the literature that labour mobility may act as a channel for knowledge spillover between firms (see Glass and Saggi 2002, and Fosfuri, Motta, and Ronde 2001 as examples). According to this effect, workers absorb some of the productive knowledge and ideas of their current employer while working on the job. Because knowledge is a non-rival good and not all knowledge can be protected, when a firm hires a worker with experience at another firm, it not only hires more labour input but also a stock of new ideas and knowledge. These ideas can be implemented by the hiring firm to augment their current production process.

Assuming adjustment costs are low enough and hiring firms have sufficient capacity to absorb the new knowledge, if labour mobility acts as a channel for productive knowledge spillover then hiring new workers from more productive firms should increase the hiring firm's stock of productive knowledge and hence productivity. Furthermore, the size of the productivity gain at the hiring firm should be positively correlated with the productivity of the new worker's previous employer. In the context of the model this effect would imply a positive coefficient for the productivity gap related to hires from more productive firms, i.e. $\beta_M > 0$.

Stoyanov and Zubanov (2012) argue that because firms are able to freely disregard any new knowledge that is less productive than the firm's current knowledge (e.g. a less efficient production technique), productive knowledge spillover from less productive firms should have very little impact on the hiring firm's performance. Therefore we should expect the productivity gap related to hires from less productive firms to have no effect, i.e. $\beta_L \approx 0$.

The amount of knowledge that workers are able to absorb and transmit is likely to be related to characteristics of the workers such as education, job type, or tenure. The ability of firms to absorb and implement new ideas may also be a factor in the spillover of knowledge. Therefore, we would expect to find larger spillover effects when the firm or worker have characteristics that could plausibility improve the ability of either to diffuse knowledge between firms.

Finally, if hiring firms are able to select workers for their knowledge when hiring, it is possible that we may not see any correlation between the productivity of the new worker's previous employer and the productivity gain at the hiring firm ($\beta_M \approx \beta_L \approx 0$). However, we would still expect that hiring intensity would be correlated with the amount of knowledge spillover, and therefore the productivity gain at the hiring firm. Therefore, finding $\lambda_s > 0$ could also be considered consistent with the knowledge spillover channel.

3.4.2 Signal of unmeasured worker quality

The regression model includes a control for the change in quality of the average worker ($\Delta Q_{j,t}$) which will be influenced by the quality of new workers arriving at the firm. As discussed in the next section, the measure of worker quality used in this analysis is derived from the worker's observed earnings across all jobs. However, there may be aspects of worker quality that are not capture by a worker's wage. For example, labour market frictions or monopolistic power for the firm will mean that a worker's wage may not accurately reflect the worker's marginal product of labour. Therefore, there may be some unmeasured component of worker quality that the data does not account for.

If there is some unmeasured component of worker quality, there are multiple ways in which one might expect it to be correlated with firm productivity. One possibility is that high productivity firms are able to better screen and hire new candidates that are of high quality. Such a process would produce positive assortative matching between skilled workers and productive firms in the style of the work by Becker (1973).[10] Alternatively, productive firms might have better quality workers because they provide better on-the-job training or facilitate within-firm learning spillovers generated through interacting with the higher quality workforce already employed by the firm (see Nix 2015).

When the previous employer's productivity provides a signal of a new hire's unmeasured quality, then hiring from more productive firms should raise the unmeasured quality of employed workers (and the hiring firm's productivity), and hiring from less productive firms should lower the unmeasured quality of employed workers. I.e. $\beta_M > 0$ and $\beta_L > 0$. Furthermore, the magnitudes of the coefficients β_M and β_L should be approximately equal as hiring from symmetrically more or less productive firms should have a similar sized effect on the firm (but with opposite signs).[11]

4. Data

Information regarding firms comes from the Longitudinal Business Database (LBD) which combines a range of survey and administrative data sources for all economically significant businesses in New Zealand.[12] Information on employees comes from the Integrated Data Infrastructure (IDI) which links employers to employees via Pay-As-You-Earn (PAYE) tax records for each job, and also contains a wide range of other survey and administrative data sources on individuals linked by anonymised individual identification numbers.

10 Most of the empirical work exploring firm-worker assortative matching has used two-way fixed effects regressions on wage data (see Abowd et al. 2004 as an example). However, this work does not measure firm productivity data directly.

11 The unmeasured worker quality channel may be sensitive to selection bias if the type of workers who select to leave more and less productive firms is not the same. Table 4 indicate that the average worker leaving more productive firms and the average worker leaving less productive firms both tend to be drawn from the lower part of the firm's earnings distribution, and move to similar rankings within the hiring firm (on average). This suggest that selection bias may not be a significant concern.

12 The term 'economically significant' encompasses firms that meet *at least one* of the following criteria: (i) More than $30,000 annual GST expenses or sales; (ii) more than three paid employees; (iii) in a GST exempt industry; (iv) part of a Business Register group of firms with ownership links; (v) a new GST registered firm. For more information on firm data in the LBD see Fabling and Sanderson (2016).

The main analysis is conducted at the firm-year level. Firm-level financial year data is mapped to the nearest tax year ending March. The sample period for the analysis is from 2001 to 2013. Below is a summary of the data and key variables used in the paper.

4.1 Firm data

The unit of measurement for a firm is a Permanent Enterprise (PENT), as defined and developed by Fabling (2011). The PENT identifier is based on the firm identifier in the LBD, and corrects for certain events such as the change in the legal status of a firm. The scope of this analysis is restricted to private-for-profit businesses within the measured sector identified by Statistics New Zealand.[13] Only for these types of businesses do we believe that revenue and cost data will provide a suitable indicator for productivity.

For the main line of analysis, the MFP of firms is measured using both a Cobb-Douglas and trans-log production function using the estimates derived by Fabling and Maré (2015b). The MFP measures are estimated on annual data reflecting the fact that the survey and tax information on revenue and expenditures is only available at this frequency. The parameters of each production function are also allowed to vary across industries. In total, 39 separate industry classifications are used to cover all firms in the measured sector, similar in detail to level 3 of the ANZSIC06 New Zealand Standard Industrial Output Categories (NZSIOC).

In addition to the MFP measures of productivity, we also consider a measure of labour productivity computed as the (real) value added per worker. The measures of real output, materials, and labour used here are taken from the same LBD sources as those used by Fabling and Maré (2015b) to compute the MFP measures of productivity.[14]

According to Fabling and Maré (2015b), there are an average of 353,766 PENTs per year in the LBD with positive employment. Of these, around 83 percent (292,978) are in the measured sector. Of the PENTs in the measured sector, around 32 percent are excluded from our sample because they lack the necessary production information to estimate productivity. Finally, the productivity of very small firms is likely to be imprecisely measured, while measures of worker turnover in small firms can be both lumpy and extreme. Therefore, the scope of analysis is further restricted to only consider productivity growth for firms that employ an average of at least ten full time employees over the year. For the construction of the productivity gap, we allow the firm size of the worker's previous employer to be as low as an average of five full time equivalent workers.[15]

[13] Private-for-profit businesses broadly covers private producer enterprises, central and local government enterprises (i.e. trading departments of the government and State-Owned Enterprises), and private financial institutions. Notable exclusions include private households (including private production), government administration and defense, and private financial businesses. See Fabling and Sanderson (2016) for more details.

The measured sector is defined by Statistics New Zealand as "industries that mainly contain enterprises that are market producers. This means they sell their products for economically significant prices that affect the quantity that consumers are willing to purchase".

[14] The online appendix provides further summary information on the firm-level data.

[15] As shown in the online appendix, the distribution of firm size within New Zealand is heavily dominated by very small firms, matching the predictions from Zipf's law. Raising the minimum firm size from an average of one FTE worker to ten FTE workers results in dropping around 90 percent of the PENT-years in the sample. The results of the regressions do not appear to be overly sensitive to the choice of minimum firm size.

4.2 Worker data

The worker data is used for two main purposes. First, to construct a measure of the average worker quality for each firm, and second, to map the transitions of workers between firms in order to construct the productivity gap measures.

4.2.1 Worker quality

The measure of average observed worker quality for each firm ($Q_{i,t}$) is computed by weighting each worker by their contribution of total full-time equivalent (FTE) labour for the firm. The measure of individual worker quality/human capital is constructed following the approach of Hyslop and Maré (2009) who utilize two-way fixed effects regressions on wage data, as developed by Abowd, Kramarz, and Margolis (1999).

A worker's observed quality is given by the contribution of the worker fixed effect and the vector of worker-level observable characteristics to the worker's log wage, effectively stripping out the firm fixed effect and idiosyncratic error term.[16] This captures observable demographic characteristics alongside time-invariant characteristics including occupation, education and skill, and relies on an assumption that workers are fairly compensated for the value they bring to their employers.[17]

The IDI only has information on hours worked for a minority of employees. Therefore we measure the labour supplied by each worker using the full-time equivalent (FTE) estimates developed by Fabling and Maré (2015a). This approach uses information on the worker's monthly income to estimate their labour supply, taking into account information like the statutory minimum wage, the number of jobs worked by the worker in a month, and the worker's income in adjacent months. One limitation of this method is that it is likely to over-estimate the labour input for some workers such as part-time workers who are highly paid.

4.2.2 Worker transitions between firms

There are two issues that need to be addressed in mapping the transition of workers between firms in the data. First, when a new worker previously worked at multiple jobs, which firm(s) does the worker bring knowledge from? Second, because firm productivity is observed at the annual frequency, and worker transitions at the monthly frequency, what level of productivity knowledge exists at the previous employer in the month the worker leaves, and what level of productivity knowledge exists at the hiring firm in the month the worker arrives?

When workers have multiple jobs, it is assumed that the productive knowledge a new worker brings to the hiring firm comes from a single source, referred to as their "main job". A worker's main job is the one that pays the worker the most. Workers' pay will be

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The choice of different minimum firm sizes for the hiring firm and the previous employer is motivated by the fact that the analysis is not concerned with lumpy changes to firm size at the previous employer, only at the hiring firm. Therefore, by lowering the minimum firm size for the worker's previous firm when constructing the productivity gap, we can capture more of the labour flows in the economy in the measure of the productivity gap. The results do not differ much if the minimum firm size for the worker's previous employer is raised to ten.

16 The results do not differ significantly if worker quality is instead measured by only the worker fixed effect or the worker's wage less the firm fixed effect. This suggests that the productivity gap and hiring intensities in the regression are not proxying for any worker-firm match quality that can be measured through the worker's wage.

17 Some of these worker characteristics could also have been developed on-the-job experience at previous employers, such as work ethic.

correlated with the time at that particular job and the worker's position within the firm's hierarchy. Both of these factors are expected to give them more opportunities to acquire new knowledge.

The main job is determined as follows. If the worker is employed at multiple firms in the three months prior to starting their new job, the previous main job is the one from which the worker received the highest real (CPI adjusted) monthly income, for a full month's work, during this three-month window.[18]

If a new worker did not previously work at any job in the quarter before starting at their new firm, the employment history of the worker is traced back in time to the last month in which they were employed for the full month and the main job is determined from the job(s) worked in that month. The analysis does not make any allowance for depreciation of the worker's stock of knowledge and skills during jobless spells.

Because firm productivity is only observed annually, we must also address how to determine the firm's productivity in the month the worker leaves or joins a firm. If a worker leaves their previous employer in the first six months of that employer's financial year, we assume that the worker takes with them the productivity knowledge of the employer in the *previous* financial year. They do not observe/learn the firm's productivity knowledge for the current year because either it takes time for the worker to learn the new knowledge implemented this year, or the firm doesn't implement new productivity changes until part way through the year, after the employee has left. If the worker leaves in the last six months of their employer's financial year, it is assumed that the worker's productivity knowledge is based on the firm's productivity level for the current year. In the same way, when the worker starts at their new firm, if the worker joins in the first six months of a financial year, last year's productivity is used. And if the worker join in the final six months of a financial year, the current year's productivity is used.

4.3 Summary statistics

Table 2 describes the firm-year characteristics of private-for-profit firms in the sample. Across all the firms in the sample, the average size of the productivity gaps associated with hiring from more and less productive firms are similar (0.064 vs 0.060), leading to an aggregate productivity gap close to zero (0.005). This suggests that as a result of hiring, the average worker at the average hiring firm had a value add last year that is 0.5 percent higher than the hiring firm's value add last year. However, there is significant variation in the knowledge exposure measures for different firms as represented by the large standard deviation of the productivity gaps. Primarily this is due to the lumpy nature of the number of new hires each year, especially for smaller firms.

[18] The reason only months in which workers are employed for the full month are considered here is that the income for months in which the worker begins/ends a job are imprecisely measured. For example, the paying out of any outstanding annual leave in the final month will bias upwards the worker's income and not accurately reflect the work done that month.

Table 2 — Summary statistics at the firm-year level (Value-added per worker)

	Firms in sample ($FTE \geq 10$)			**Firms that hire new workers**			**Firms that hire from more productive firms**			**Firms that do not hire**		
Variable	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**
Labor productivity												
log V.A. per worker	11.102	11.094	N.A.	11.101	11.093	N.A.	10.962	10.983	N.A.	11.176	11.165	N.A.
Growth rate V.A. per worker (%)	-0.004	0.000	0.432	-0.003	0.001	0.432	-0.003	0.001	0.457	-0.040	-0.019	0.388
Productivity gap												
Aggregate gap	0.005	0	0.208	0.005	0	0.209	0.041	0.015	0.228	0	0	0
More prod. firms gap	0.064	0.015	0.164	0.065	0.016	0.165	0.100	0.046	0.196	0	0	0
Less prod. firms gap	-0.060	-0.022	0.123	-0.061	-0.023	0.124	-0.059	-0.027	0.108	0	0	0
Labor force												
Total FTE units of labor	56.230	17.961	255.994	56.953	18.166	258.128	75.169	21.743	317.416	14.248	12.181	8.657
Share of FTE from new hires	0.194	0.155	0.169	0.198	0.157	0.169	0.218	0.180	0.162	0	0	0
Share of FTE from exiting workers	0.172	0.136	0.150	0.174	0.138	0.150	0.192	0.157	0.148	0.086	0.042	0.165
Excess (annual) turnover	0.514	0.457	0.329	0.522	0.462	0.325	0.594	0.538	0.330	0.019	0	0.054
New Hires												
No. of new employees	22.070	7	101.667	22.448	7	102.498	31.686	11	125.734	0	0	0
Share of hires from brand new workers	0.001	0	0.018	0.001	0	0.018	0.001	0	0.010	0	0	0
Share of hires from non-market	0.116	0.062	0.166	0.116	0.062	0.165	0.105	0.079	0.120	0	0	0
Share of hires from small firms (L<5)	0.288	0.250	0.232	0.288	0.250	0.231	0.260	0.250	0.171	0	0	0
Share of hires from missing prod. data	0.102	0.051	0.154	0.102	0.053	0.154	0.091	0.069	0.107	0	0	0
Share of hires from PFP	0.489	0.500	0.257	0.489	0.500	0.257	0.540	0.519	0.198	0	0	0
within same industry	0.131	0.061	0.180	0.131	0.062	0.180	0.148	0.105	0.170	0	0	0
More productive sources	0.205	0.167	0.219	0.205	0.167	0.219	0.305	0.250	0.202	0	0	0
Obs.	126048			124146			80700			1902		

Notes: Summary statistics based on the sample of firm-year observations in the data set. FTE refers to Full Time Equivalent units of labour (1 FTE = 1 worker per year). Shares of hires are computed as the number of hires from the subgroup relative to the total number of new hires for that firm-year. N.A. denotes values that have been censored in accordance with Statistics New Zealand's confidentiality guidelines. PFP denotes Private For Profit firms (those for which we have productivity data). 'Firms that hire from more productive firms' denotes any firm that hires at least one worker from a more productive firm during that year.

The distribution of labour across firms is highly skewed. In the sample of firms with an average of more than 10 FTE workers, the average firm uses the equivalent of around 56 FTE employees, while the median firm employees the equivalent of around 18 FTE employees on average across the year. The average firm also features a large amount of labour churn. On average, new workers supply just under 20 percent of the FTE labour units used by a firm each year. Workers who will leave the firm sometime during the current year supply on average around 17 percent of the firm's labour. This contributes to an excess turnover rate of around 50 percent.[19]

The average firm hires around 22 new employees each year, and the overwhelming majority of firm-years feature the firm employing at least one new worker. Around 49 percent of new workers come from other PFP firms that we observe productivity data from in the data set. In addition, 13 percent of all new hires by the average firm are from PFP firms within the same industry, and around 20 percent of new hires are from more productive PFP firms.

Table 2 also describes the characteristics of the subsets of firms that hire new workers, firms that hire at least one new worker from a more productive firm, and firms that do not hire new workers. Firms that hire at least one worker tend to have slightly lower productivity than firms that do not, but are also significantly larger in terms of labour force size, and have higher rates of labour market churn.

Firms do not hire new workers randomly and there is often a lot of selection (on both sides) when forming a new employment match. Table 3 shows where firms in each productivity decile source their new workers from. Remarkably, the share of new hires from each source are very similar for firms in all of the productivity deciles. The largest single source of new employees for firms in each productivity decile are from other firms with less than five employees.

Table 3 — Worker transitions — Value-added per worker

Hiring firm's	Source of new employee hires													
	PFP productivity decile										New	Non	Firms with	PFP miss.
prod. decile	1	2	3	4	5	6	7	8	9	10	Arrivals	Market	L<5	data
1	0.05	0.08	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.00	0.16	0.30	0.08
2	0.05	0.08	0.05	0.05	0.04	0.04	0.04	0.04	0.03	0.03	0.00	0.16	0.31	0.08
3	0.04	0.07	0.06	0.06	0.04	0.04	0.03	0.03	0.03	0.03	0.00	0.16	0.32	0.08
4	0.04	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.00	0.14	0.33	0.08
5	0.04	0.06	0.05	0.05	0.05	0.04	0.04	0.05	0.04	0.04	0.00	0.14	0.32	0.08
6	0.04	0.06	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.00	0.13	0.33	0.08
7	0.04	0.06	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.00	0.13	0.32	0.08
8	0.04	0.06	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.06	0.00	0.13	0.32	0.08
9	0.04	0.05	0.03	0.03	0.04	0.04	0.04	0.06	0.06	0.08	0.00	0.13	0.31	0.08
10	0.04	0.05	0.03	0.03	0.03	0.03	0.04	0.05	0.06	0.13	0.00	0.14	0.28	0.09

Notes: Each cell shows the fraction of total hires made by all firms in each productivity decile (row) from each source (column). Sources are denoted by either their productivity decile (if the data is available), or are classified as out of scope due to the worker never being observed before (new arrivals), the sending firm being either non-market, the sending firm being a private for profit firm but too small for the sample, or there is missing productivity data for the PFP firm.
For example cell (1,1) states that firms in the lowest productivity decile hire 5 percent of their new hires from other firms in the lowest decile. Each row sums to one. Cells are shaded based upon the fraction of hires, with darker shades corresponding to a higher fraction of total hires. Deciles correspond to the firm's productivity ranking within each year, with decile 10 referring to the most productive firms.

In terms of hiring from other PFP firms for which we are able to estimate the productivity level, firms do marginally favour sourcing new workers from similar productivity deciles. However, this tendency is weak – even firms in the lowest productivity decile obtain about 4 percent of their new workers from firms in the top productivity decile. This suggests that

[19] Excess turnover is computed as

$$\text{Excess turnover} = \frac{\text{starts} + \text{exits} - |\text{net change}|}{(FTE_t + FTE_{t-1})/2}$$

where FTE is the number of full time equivalent units of labour in the final month of the firm's financial year.

the labour market is not segmented by firm productivity, and even the least productive firms still have fairly equal access to workers from the most productive firms.

Table 4 summarizes the key worker-level characteristics of new hires relative to different groups of workers. Panel A of the table shows the characteristics of new workers relative to the average incumbent worker in the hiring firm, one month after hiring. The average new worker earns an FTE income that is roughly 85 percent of the average incumbent worker at the hiring firm. Workers sourced from more productive firms tend to earn marginally more than workers from less productive firms (84.5 vs 86.2 percent of the average incumbent's earnings). New workers tend to be younger (about 88 percent of the average age) than the average incumbent, and less skilled (around 87 percent of the worker quality of the average incumbent worker). New workers are also more likely on average to be multiple job-holders, working an average of 10 percent more jobs in the same month.[20]

Panel B of Table 4 shows the characteristics of new workers relative to the average worker at their previous main job (in the month prior to them leaving). On average, workers who change jobs tend to earn around 86 percent of the average FTE pay, supply 88 percent of the average FTE units, and also be younger and less skilled than the average worker. These results do not differ dramatically whether we consider workers coming from more or less productive firms. It is likely that the general negative selection in workers who leave firms may reflect the proportionally higher job mobility by younger/junior employees.

Panel C shows the worker's characteristics at their new job, relative to their last main job. A worker's FTE-adjusted monthly earnings are around 13 percent higher in their new job, and they supply around twice the FTE units of labour. This large increase in labour supply is primarily driven by part-time workers and those with multiple jobs transitioning to full-time jobs. The median worker supplies the same number of hours at their new job as they did at their previous job. The average new employee has an average of just over five months break between jobs, with a median break of zero months. Given that we de not model any depreciation of skill or knowledge for long employment breaks, such a short duration between jobs is desirable.

Overall, workers who move between firms tend to come from the lower half of the sending firm's pool of labour (in terms of earnings, age, and labour supplied), and they also tend to have a similar ranking in the firms that they join. If knowledge spillover or unmeasured worker quality is related to observable characteristics of the workers, this relationship is likely to bias our baseline results downwards.

[20] This calculation excludes the month they joined the new firm, but may in part reflect delayed payments from their previous employer.

Table 4 — Summary statistics for new workers

	All new hires			New hires from more productive firms			New hires from less productive firms		
Variable	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**
A) New worker's characteristics (at the hiring firm) relative to incumbent workers									
Real earnings percentile	0.450	0.407	0.309	0.422	0.369	0.303	0.464	0.438	0.305
FTE supplied relative to avg. incumbent	0.903	1.003	0.690	0.904	1.002	0.616	0.918	1.008	0.715
Age relative to avg. incumbent	0.889	0.825	0.343	0.899	0.835	0.343	0.860	0.793	0.332
Worker quality percentile	0.490	0.478	0.299	0.460	0.429	0.293	0.511	0.500	0.295
Number of jobs relative to avg. incumbent	1.141	0.975	0.533	1.135	0.971	0.535	1.130	0.975	0.486
Obs.	4094400			1154500			1335200		
B) New worker's characteristics (at last main job) relative to the workers who stays									
Real earnings percentile	0.450	0.407	0.309	0.422	0.369	0.303	0.805	0.713	0.612
FTE supplied relative to avg. stayer	0.920	1.001	1.456	0.980	1.015	0.939	0.883	1	0.858
Age relative to avg. stayer	0.879	0.813	0.345	0.889	0.825	0.345	0.850	0.783	0.334
Worker quality percentile	0.490	0.478	0.299	0.460	0.429	0.293	0.511	0.500	0.295
Number of jobs relative to avg. stayer	1.145	0.972	0.546	1.131	0.965	0.543	1.139	0.974	0.504
Obs.	4005200			1131200			1314900		
C) New worker's characteristics at their new job relative to their own characteristics at the last main job									
Real earning per FTE	1.119	1.025	0.494	1.064	1.002	0.459	0.464	0.438	0.305
FTE supplied: new job relative to old job	2.346	1	228.217	2.178	1	205.699	2.532	1	330.921
No. of months between jobs	5.484	0	13.167	4.823	0	11.572	4.630	0	11.539
Prob. working in same industry	0.226	0	0.418	0.284	0	0.451	0.275	0	0.447
Obs.	4202000			1180200			1367800		

Notes: Summary statistics are computed at the worker-month level. Percentiles refer to the percentile within the firm (e.g. 0.45 implies the new worker is above 45 percent of workers in the firm). Statistics that are reported as relative to the average are computed as a fraction relative to the average member of the control group (e.g. 0.5 implies that the new worker's characteristic is half that of the average control group member). Worker quality is defined in section 4.2. FTE denoted Full Time Equivalent measure of labour. Real earnings are computed controlling for FTEs supplied.

5. Analysis

The regression analysis is carried out in three stages. Section 5.1 analyses the baseline model. Section 5.2 extends the baseline model by disaggregating the productivity gaps further. Section 5.3 considers issues to do with robustness.[21]

5.1 Baseline model

Table 5 presents the initial regression results starting with a model where changes in firm productivity are driven only by changes in the quality of the labour force (column 1) and building up to the baseline model with separate productivity gaps for hires from more and less productive firms, defined by (4) and (8), in the final column. All results in the table are computed using value-added per worker as the productivity measure.

The first specification in Table 5 shows that the change in the firm's productivity is significantly correlated with the change in the (measured) quality of the average worker within the firm (ΔQ_i). According to the estimation, improving the quality of the average worker by 1 percent would be associated with average increase in labour productivity of around 0.5 percentage points.

Adjusting the average quality of a firm's labour through hiring is likely to incur different costs to the firm than adjusting through firing or changing the hours of incumbent workers. For example, newly hired workers may take time to adjust and fit to the culture of the firm. This can mean the effect of adjusting average worker quality through new hirings on productivity growth is different to other adjustment margins. In the remaining specifications in the table, the change in average worker quality is decomposed into the contributions from new hires, workers who leave the firm, and incumbent workers.[22]

The specification in the second column of Table 5 shows the effects of this decomposition. While the effect of new workers is statistically different from the effect of the quality of labour through exiters and incumbents (p-value=0.000), the practical difference is small. A one percent increase in the quality of workers due to new hires raises the firm's productivity growth by 0.416 percentage points on average, while a one percent increase due to incumbent workers would raise the firm's productivity growth by 0.431 percentage points on average. We also see similarities in the magnitudes between the effect of the quality of new workers relative to incumbent workers for the other specifications shown in Table 5. This suggests that costs (in terms of the firm's productivity) associated with on-boarding new workers are not significant relative to the costs associated with improving the firm's average quality of labour via changes to the mixture of hours worked by incumbent employees.

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21 Other regression specifications are presented in the online appendix.

22 More formally, let N denote new workers that join the firm in year t, I denote incumbent workers who work for the firm in both years t and $t-1$, and X denote workers who exit the firm between years $t-1$ and t. The change in worker quality can be equivalently written as:

$$\Delta Q_{i,t} = s_{N,t}Q_{N,t} - s_{X,t-1}Q_{X,t-1} + s_{I,t}Q_{I,t} - s_{I,t-1}Q_{I,t-1}$$

where $s_{A,\tau}$ denotes the share of labour for workers of type A at time τ, and $Q_{A,\tau}$ denotes the average quality of workers of type A at time τ within the firm. In the context of Table 5, the contribution from new hires is given by $s_{N,t}Q_{N,t}$, the contribution from those who exit is given by $-s_{X,t-1}Q_{X,t-1}$, and the contribution from incumbents is given by $s_{I,t}Q_{I,t} - s_{I,t-1}Q_{I,t-1}$.

Table 5 — Initial regression results

	Aggregate $\Delta Q_{i,t}$	$\Delta Q_{i,t}$ decomp.	Add share of new hires: All new hires	Add share of new hires: more/less decomp.	Add productivity gap: Aggregate prod gap	Add productivity gap: more/less decomp.	Add prod lags: Aggregate prod gap	Add prod lags: more/less decomp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Q_{i,t}$	0.507***							
	(0.051)							
$\Delta Q_{i,t}$ due to (γ):								
New hires		0.416***	0.432***	0.380***	0.359***	0.385***	0.467***	0.479***
		(0.051)	(0.050)	(0.050)	(0.050)	(0.049)	(0.076)	(0.075)
Exiters		0.407***	0.414***	0.366***	0.348***	0.373***	0.456***	0.468***
		(0.051)	(0.050)	(0.050)	(0.050)	(0.049)	(0.076)	(0.075)
Incumbents		0.431***	0.449***	0.396***	0.376***	0.402***	0.481***	0.494***
		(0.051)	(0.050)	(0.050)	(0.050)	(0.049)	(0.076)	(0.075)
Hire intensity (λ):								
New entrants			0.101	0.134	0.129	0.103	-1.466	-1.397
			(0.344)	(0.337)	(0.329)	(0.325)	(1.391)	(1.391)
Out of scope firms			-0.015	-0.052***	-0.071***	-0.071***	-0.085***	-0.091***
			(0.018)	(0.018)	(0.019)	(0.019)	(0.028)	(0.029)
Small PFP firms			-0.057***	-0.072***	-0.081***	-0.076***	-0.025	-0.024
			(0.015)	(0.014)	(0.014)	(0.014)	(0.022)	(0.022)
PFP firms missing data			-0.107***	-0.112***	-0.093**	-0.108***	-0.116**	-0.127**
			(0.036)	(0.034)	(0.029)	(0.032)	(0.047)	(0.050)
Observed PFP firms			-0.034***		-0.048***		-0.060***	
			(0.009)		(0.011)		(0.015)	
More prod. PFP firms				0.205***		-0.241***		-0.200***
				(0.014)		(0.043)		(0.057)
Less prod. PFP firms				-0.294***		-0.118***		-0.117***
				(0.018)		(0.020)		(0.027)
Excess turnover:			0.051***	0.046***	0.042***	0.044***	0.042***	0.044***
			(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)
Productivity gap (β):								
Aggregate gap					0.354***		0.281***	
					(0.022)		(0.027)	
More prod. firms						0.585***		0.480***
						(0.069)		(0.098)
Less prod. firms						0.165***		0.153***
						(0.020)		(0.030)
$\Delta \ln A_{i,t-1}$							-0.073**	-0.038
							(0.029)	(0.026)
Includes:								
Industry-year F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Lagged productivity	no	no	no	no	no	no	yes	yes
Parameter tests:								
$\Pr(\beta_M = \beta_L)$						0.000		0.001
$\Pr(\lambda_M = \lambda_L)$				0.000		0.020		0.237
$\Pr(\gamma_{new} = \gamma_{incmb})$		0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs.	89592	89592	88062	88062	84885	88062	36291	37269

Notes: The dependent variable $\Delta \ln A_{i,j,t}$. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The specifications in the third and fourth columns of Table 5 add to the model the hiring intensities from various sources, as well as the control for excess turnover. The coefficients on these hiring intensity variables can be interpreted as the average percentage point change in next period's productivity from hiring one percent of the labour force from that particular source, holding all else equal. In general, the coefficients are negative and suggest that hiring one percent of the firm's labour force from any of the sources usually lowers firm productivity in the region of 0.1 percentage points. The coefficients on excess turnover are positive, but small.[23] The coefficient estimates suggest that excess hires on the order of 10 percent of the firm's FTE labour supply is associated with a 0.4 percentage

[23] One possible reason why productivity growth is positively correlated with excess turnover is firms may be replacing workers who depart sunset departments within the firm with new hires in sunrise departments (with higher productivity).

point increase in the growth rate of productivity.

The decomposition of the hiring intensities from PFP firms into hires from more productive PFP firms and hires from less productive PFP firms in column four yields an interesting insight into the small coefficient for the aggregate hire intensity from PFP firms (-0.034) seen in column three. Hiring new workers from more productive PFP firms leads to an increase, on average, of the hiring firm's productivity growth. This increase is in the order of 0.2 percentage points when hiring one percent of the work force from more productive PFP firms. However, hiring one percent of all workers from less productive PFP firms is associated with a decrease, on average, in the order of around 0.3 percentage points. By hiring new workers from a mixture of more and less productive PFP firms, the productivity gains from hiring from more productive sources are offset by the productivity losses from hiring from less productive sources. As a result, the average effect from hiring from PFP firms is relatively small. It is very likely that a similar offsetting is occurring in hiring from other sources. However, because we cannot observe the productivity of firms in these other sources, it is not possible to say with certainty.

The regressions in columns five and six of Table 5 add to the model the productivity gap variables, completing the inclusion of our proxy measure for the change in the firm's stock of productive knowledge. When considering hires from PFP sources in aggregate (column five), the coefficient on the aggregate productivity gap (β_2) suggests that for a firm that has a hiring intensity (H/L) from PFP sources of 10 percent, raising the average productivity of the PFP firms that workers are sourced from by one percent would be associated with an average 0.35 percentage point increase in productivity growth for the hiring firm.[24] Column six shows that if we disaggregate the productivity gap into separate productivity gaps for hires from more and less productive firms, the productivity gain (intensive margin) associated with the productivity gap for hiring from more productive firms is twice as large as the productivity loss associated with hiring from symmetrically less productive firms.

The final two specifications in Table 5 include the lagged productivity dynamics of the hiring firm and represent the baseline model. In practice, most of the coefficients are not significantly affected by the inclusion of productivity lags. The coefficients related to the change in worker quality are slightly larger, and the coefficients related to the productivity gaps are slightly smaller, but the differences are relatively small.

The fact that the coefficients on the productivity gaps for hires from both more and less productive firms are both positive and significant is consistent with an unmeasured worker quality channel (which predicts that hiring from even more productive firms should raise the unmeasured worker quality within the firm, and hiring from even less productivity firms should lower it). In addition, the fact that the coefficient on the productivity gap associated with hires from more productive firms is significantly larger than that on the productivity gap associated with hires from less productive firms is consistent with the productive knowledge spillover story.

If we were to assume that both the signal of unmeasured worker quality channel and the productive knowledge spillover channel were occurring simultaneously, this assumption would suggest that the size of the knowledge spillover premium for hiring from more productive firms would be equal to 0.33, the difference between the two coefficients (0.48-0.15). This implies that a little over two thirds of the improvement associated with the increase in the average source's productivity would be due to the knowledge spillover,

[24] As an alternative interpretation of the coefficient, one could view the coefficient through the lens of the average worker's exposure to better productivity. Hiring from other PFP sources such that the average worker within the firm has previous productivity knowledge one percent greater than the hiring firms productivity will raise the productivity growth in the hiring firm by 0.35 percentage points on average.

and around one third would be due to improvements in the unmeasured worker quality.

Labour productivity, or value-added per worker, is only one possible measure of firm productivity. Table 6 compares the estimated key parameters from the baseline model using value-added per worker to the estimated values found using various MFP measures of firm productivity. The coefficients related to the productivity gaps for all productivity measures are positive and significant in magnitude. In the case of the Cobb-Douglas measure of MFP, the coefficient related to the productivity gap from less productive firms is around 40 percent larger than the coefficient related to the productivity gap from more productive firms (0.374 compared to 0.271). However this difference is not significantly (p-value = 0.22). In the case of the trans-log based measure of productivity (whose specification nests the Cobb-Douglas), the coefficients on the two productivity gaps are very similar, both economically as well as statistically (p-value = 0.8).

Table 6 — Baseline regression results for various productivity measures

	Value-added	**Cobb-Douglas**	**Trans-log**
Productivity gap, hires from (β):			
More prod. Firms	0.480***	0.271***	0.354***
	(0.098)	(0.065)	(0.068)
Less prod. Firms	0.153***	0.374***	0.374***
	(0.030)	(0.054)	(0.056)
Hire intensity (λ):			
More prod. firms	-0.200***	-0.012	-0.037*
	(0.057)	(0.028)	(0.021)
Less prod. Firms	-0.117***	0.047*	0.004
	(0.027)	(0.026)	(0.019)
$\Delta Q_{i,t}$ due to (γ):			
New hires	0.479***	0.105*	0.162***
	(0.075)	(0.062)	(0.049)
Exiters	0.468***	0.103*	0.159***
	(0.075)	(0.062)	(0.048)
Incumbents	0.494***	0.110*	0.166***
	(0.075)	(0.062)	(0.048)
Parameter tests:			
$\Pr(\beta_M = \beta_L)$	0.001	0.217	0.808
$\Pr(\lambda_M = \lambda_L)$	0.237	0.145	0.174
$\Pr(\gamma_{new} = \gamma_{incmb})$	0.000	0.037	0.026
Obs.	37269	28260	38037

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. When included in the regression, $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Additionally, the coefficients related to the hire intensity (λ_s) from more and less productive firms are no longer significantly negative when using the MFP measures of productivity, and are very close to zero. In fact for the Cobb-Douglas measure of productivity, the coefficient on the hiring intensity from less productive firms is slightly positive. However, in general the hiring intensities do not seem to have a significant influence on productivity growth when using MFP to measure firm productivity.

For all productivity measures, even after controlling for observed worker quality, the coefficients on the productivity gaps are positive, implying that raising the productivity of the average PFP firms that workers are sourced from leads to higher productivity growth on average. This finding supports the idea of an unmeasured worker quality channel (which predicts both coefficients should be positive and equal). This is especially true for the MFP measures of firm productivity where the coefficients on the productivity gaps relating to hires from more and less productive firms are not statistically different.[25]

Only the baseline model estimated using value-added per worker as the measure of firm productivity provides support for the predictions of the knowledge spillover channel (which predicts a larger coefficient on the productivity gap associated with hires from more productive firms). One of the potential reasons why we see this support in the value-added productivity measure and not the MFP based measures is that the MFP measures of productivity control for the use of capital and materials. If firms that hire workers from other firms with higher labour productivity end up increasing their own capital intensity, this hiring would appear as an increase in labour productivity, but not necessarily as an increase in MFP.[26] Therefore, if the larger coefficient on the productivity gap for hires from more productive firms seen in the value-added results does relate to a knowledge spillover channel, it is likely that the knowledge relates to production technology (the functional form of the production function, or how capital intensive the production process is), rather than the strict multi-factor productivity of the firm.

To investigate this hypothesis further, the baseline model is re-estimated using the firm's ratio of capital to labour as the dependent variable instead of firm productivity. Table 7 summarizes the key coefficients from this regressions. The coefficients related to the input intensity gap (the replacement for the productivity gap) for hires from more capital-intensive firms is around twice as large as the coefficient related to the input intensity gap for hires from less input-intensive firms. This suggests that there is an increase in input-intensity associated with hiring from firms that are more input-intensive, matching the pattern seen in the productivity gap coefficients for the value-added measure of firm productivity.[27]

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25 Estimating the model separately for each industry reveals that the baseline results are fairly consistent across the largest industries in the data set. Therefore, the results are not being biased by one particular industry.

26 Another possibility is the fact that the MFP measures fail to capture the productivity level differences between industries. This issue is explored further in the following subsection.

27 Another possible driver of the differences between the value-added and MFP results is that MFP measures of productivity are constructed relative to an industry-year average. Hence, when constructing the productivity gap using MFP measures, we fail to capture any between-industry productivity differences, which the value-added measure of labour productivity would capture. This issue is explored further in the online appendix by re-estimating the model on demeaned value-added data. The results do not differ significantly from the regular value-added results, suggesting that the demeaned nature of MFP measures is not the main driver of the differences between the results using value-added and MFP measures.

Table 7 — ***Baseline results for capital-labour ratio measure***

	Capital-Labor
Input intensity gap, hires from (β):	
More capital-intensive firms	0.047***
	(0.017)
Less capital-intensive firms	0.021
	(0.024)
Hire intensity (λ):	
More capital-intensive firms	0.071**
	(0.031)
Less capital-intensive firms	-0.182***
	(0.035)
$\Delta Q_{i,t}$ due to (γ):	
New hires	0.568***
	(0.075)
Exiters	0.558***
	(0.075)
Incumbents	0.608***
	(0.075)
Parameter tests:	
$\Pr(\beta_M = \beta_L)$	0.369
$\Pr(\lambda_M = \lambda_L)$	0.000
$\Pr(\gamma_{new} = \gamma_{incmb})$	0
Obs.	28260

Notes: The dependent variable in the regressions is the change in log capital-labour ratio ($\Delta \ln(K_{i,j,t}/L_{i,j,t})$). Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln \ln(K_{i,j,t-1}/L_{i,j,t-1})$ is instrumented for using $\ln(K_{i,j,t-2}/L_{i,j,t-2})$ in response to the presence of Nickell bias. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To summarize the findings of the baseline regressions: while the baseline results do not imply causality or provide definitive conclusions regarding the channels through which new workers benefit hiring firms, they do point us towards the likely channels which would be consistent with the findings. For all of the firm productivity measures considered, both labour productivity and MFP measures, the coefficients on the productivity gaps for hires from more and less productive firms are both positive and significant. Therefore, all else equal, when hiring from other private-for-profit (PFP) firms, raising the average productivity of the firms workers are sourced from is associated with improved productivity growth during the next year. This pattern is consistent with the idea of an unmeasured worker quality component in which worker quality is unobserved by the econometrician but is signalled to the hiring firm through the productivity of the worker's previous employer.

In the specific case of labour productivity, the coefficient on the productivity gap for hires from more productive firms is more than twice as large as the coefficient on the productivity gap from less productive firms. This would suggest that there is a premium (over and above the unmeasured worker quality channel) from hiring from more productive firms, consistent with the predictions of a knowledge spillover channel. However, once we move to looking at firm productivity through the lens of MFP measures, this premium disappears. By estimating the model on the capital-labour ratio, we see that there is also an input-intensity gap premium associated with hiring from more input-intensive sources. This, combined with the MFP findings, suggests that if the productivity gap premium is being driven by a knowledge spillover effect, the knowledge specifically refers to knowledge regarding production technology (the functional form of the production function) rather than multi-factor productivity knowledge. In other words, firms are able to adopt more input-intensive production techniques using the knowledge of workers with more experience in these approaches.

5.2 Extensions to the model

In this section the baseline model will be extended to consider how various firm and worker characteristics influence the productivity gap and hiring intensity coefficient estimates. These extensions are based on the predictions made by the various channels of worker benefit considered by the analysis, and will provide further checks on the strength of support for the channels found so far.

5.2.1 Industry-specific knowledge

If workers facilitate the spillover of knowledge between firms, not all knowledge that workers bring into the firm will be of equal value. The structure of the baseline model already allows for different effects from knowledge coming from more and less productive firms through the disaggregated productivity gaps. However, this dimension is not the only dimension along which the value of knowledge will differ for the hiring firm. For example, workers with knowledge that relates to the market in which the hiring firm operates or knowledge that is able to complement the hiring firm's current stock of productive knowledge are likely to have a greater effect on firm productivity than workers with other types of knowledge. Therefore, the knowledge spillover channel predicts that workers hired away from other firms within the same industry (whose knowledge should be more valuable to the hiring firm) would have a larger benefit for the hiring firm's productivity than workers hired away from firms in other industries.

To examine if this is the case, the productivity gaps (and hire intensities) related to hires from more and less productive PFP firms are further subdivided into two groups: hires from within the same industry, and hires from different industries, i.e.:

$$\begin{aligned}\mathrm{Exoposure}_{i,t} \quad &= \sum_{\mathrm{ind}\in\{\mathrm{same,diff}\}} \beta_{M,\mathrm{ind}} \frac{\sum_{n\in\mathcal{N}^M_{j,t-1}} \mathbb{D}_{\mathrm{ind}}(n)[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\ &+ \sum_{\mathrm{ind}\in\{\mathrm{same,diff}\}} \beta_{L,\mathrm{ind}} \frac{\sum_{n\in\mathcal{N}^L_{j,t-1}} \mathbb{D}_{\mathrm{ind}}(n)[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\ &+ \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}, \end{aligned} \tag{9}$$

where '$\mathrm{ind} = \mathrm{same}$' denotes the hire is from the same industry, '$\mathrm{ind} = \mathrm{diff}$' denotes the hire is from a different industry, $\mathbb{D}_{\mathrm{ind}}(n)$ is a dummy variable based on the 'ind' classification. So when $\mathbb{D}_{\mathrm{ind}}(n) = \mathbb{D}_{\mathrm{same}}(n)$, $\mathbb{D}_{\mathrm{same}}(n)$ takes on the value of 1 if worker n's previous main job was in the same industry as the hiring firm (and a similar definition for the case when '$\mathrm{ind} = \mathrm{diff}$'). Therefore, $\beta_{M,\mathrm{same}}$ denotes the effect of the productivity gap for hires from more productive firms within the same industry. In addition, the set of sources, $\mathcal{S}_{i,t-1}$, is expanded to include hires from the same and different industries who worked at more or less productive firms.

Table 8 presents the key results for estimating this extended version of the model for the three main productivity measures. There are 39 different industries within the data set (at roughly a 3-digit level of classification). With such a narrow definition of same industry, there is the possibility that the knowledge from other closely related industries might also be highly applicable, and this effect will be lost when aggregating hires from other relevant industries with those from less relevant industries.[28] Therefore, Table 8 also provides results for when the definition of same industry is based on industry groups aggregated to the 1-digit level (e.g. all manufacturing industries are grouped together).

Table 8 shows that when value-added per worker is used to measure firm productivity, the coefficient on the productivity gap from workers from more productive firms within the same industry is nearly three times as large as the coefficient on the productivity gap from workers from more productive firms in other industries (the p-value is 0.03). The coefficients on the productivity gap from less productive firms are (i) significantly lower then the coefficients on the productivity gap from more productive firms and (ii) not significantly different between hires from the same and hires from different industries. Relative to the baseline results, this pattern in productivity gap coefficients supports the predictions of a productive knowledge spillover channel that productive knowledge from within a firm's own industry is more applicable to the hiring firm and provides a larger boost to firm productivity than productive knowledge from outside the industry. Less productive knowledge, whether from inside or outside the firm's industry, is less useful to the hiring firm, and will likely be discarded.

For both of the MFP measures considered, the coefficients related to the productivity gaps from hires in the same industry are not significantly different from those related to hires from different industries (or the baseline results that do not distinguish between industries). This broadly lines up with the prediction from the unmeasured worker quality channel that the benefit to the hiring firm is unlikely be affected by the industry the worker previously worked in, given that it is hard to motivate how there will be a systemic difference in the ability of firms to screen or train workers within and between industries.[29]

The remaining parameters in the model are generally not significantly affected by the distinction between hires from within or between industries. Most notably, the coefficients related to the hire intensities from the various sources do not differ significantly with hiring from the same or different industries.[30]

[28] For example, the 'Sheep, beef cattle, and grain farming' industry and the 'Dairy cattle farming' industry appear as separate industries in the data at the 3-digit level, but likely share some common knowledge base.

[29] An exception to this prediction would be if unmeasured worker quality was related to on-the-job training, and workers received training that was industry specific. In such a case, we would expect to see some differences in the coefficients related to the same and different industries.

[30] The result that the coefficients on the productivity gap of hires from different industries are similar to those of hires from the same industry also supports the argument that the use of MFP measures (which are mean-zero within industries) does not seem to be causing significant bias to the results.

Table 8 — Regression results featuring between and within industry productivity gaps

	Value-added			Cobb-Douglas			Trans-log		
	Baseline	Productivity gaps by ind.		Baseline	Productivity gaps by ind.		Baseline	Productivity gaps by ind.	
		3-digit	1-digit		3-digit	1-digit		3-digit	1-digit
Prod. gap, hires from (β):									
More prod. firms	0.480***			0.271***			0.354***		
	(0.098)			(0.065)			(0.068)		
Within same ind.		1.016***	0.926***		0.234*	0.156		0.311**	0.287***
		(0.230)	(0.164)		(0.137)	(0.099)		(0.123)	(0.105)
From diff. ind.		0.367***	0.326***		0.296***	0.350***		0.373***	0.390***
		(0.123)	(0.121)		(0.088)	(0.100)		(0.090)	(0.097)
Less prod. firms	0.153***			0.374***			0.374***		
	(0.030)			(0.054)			(0.056)		
Within same ind.		0.188***	0.156***		0.565***	0.572***		0.278***	0.314***
		(0.068)	(0.052)		(0.142)	(0.110)		(0.103)	(0.079)
From diff. ind.		0.139***	0.152***		0.319***	0.286***		0.415***	0.418***
		(0.035)	(0.039)		(0.065)	(0.074)		(0.071)	(0.086)
Hire intensity (λ):									
More prod. firms	-0.200***			-0.012			-0.037*		
	(0.057)			(0.028)			(0.021)		
Within same ind.		-0.310***	-0.312***		0.036	0.042		0.008	0.002
		(0.075)	(0.064)		(0.042)	(0.035)		(0.028)	(0.028)
From diff. ind.		-0.168*	-0.154*		-0.037	-0.055		-0.059**	-0.066**
		(0.078)	(0.081)		(0.038)	(0.044)		(0.028)	(0.031)
Less prod. firms	-0.117***			0.047*			0.004		
	(0.027)			(0.026)			(0.019)		
Within same ind.		-0.069	-0.099***		0.089*	0.088**		-0.001	-0.005
		(0.040)	(0.035)		(0.046)	(0.038)		(0.028)	(0.023)
From diff. ind.		-0.139***	-0.120***		0.031	0.028		0.004	0.010
		(0.033)	(0.037)		(0.032)	(0.037)		(0.025)	(0.029)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.001			0.217			0.808		
$\Pr(\beta_{M,\text{same}} = \beta_{L,\text{same}})$		0.001	0.000		0.080	0.004		0.825	0.832
$\Pr(\beta_{M,\text{diff}} = \beta_{L,\text{diff}})$		0.064	0.159		0.833	0.600		0.712	0.824
$\Pr(\beta_{M,\text{same}} = \beta_{M,\text{diff}})$		0.029	0.005		0.728	0.214		0.724	0.517
$\Pr(\beta_{L,\text{same}} = \beta_{L,\text{diff}})$		0.531	0.955		0.138	0.048		0.302	0.406
$\Pr(\lambda_M = \lambda_L)$	0.237			0.145			0.174		
$\Pr(\lambda_{M,\text{same}} = \lambda_{L,\text{same}})$		0.008	0.006		0.418	0.389		0.846	0.851
$\Pr(\lambda_{M,\text{diff}} = \lambda_{L,\text{diff}})$		0.748	0.733		0.202	0.177		0.111	0.095
$\Pr(\lambda_{M,\text{same}} = \lambda_{M,\text{diff}})$		0.228	0.117		0.228	0.104		0.124	0.117
$\Pr(\lambda_{L,\text{same}} = \lambda_{L,\text{diff}})$		0.169	0.659		0.305	0.270		0.895	0.694
Obs.	37269	37269	37269	28260	28260	28260	38037	38037	38037

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$, where the measure of productivity differs by column. The 3-digit classification refers to the level of industry classification used by Fabling and Maré (2015b) which is very similar to the level 3 ANZSIC06 categories. The 1-digit classification refers to the level 1 ANZSIC06 categories. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2.2 Tenure

Workers who have been at their previous employer for a long period of time are more likely to have acquired knowledge about the productivity practices of that firm, more likely to have received on-the-job training, and more likely to have had a good fit with their employer.

According to the knowledge spillover channel, workers who have a longer tenure at their previous employer should have more opportunities to observe and learn what makes their employer productive. As a result, the amount of knowledge spillover from more productive firms should be positively correlated with the length of tenure at the previous firm. Workers from less productive firms are not likely to be transmitters of knowledge between firms (as this knowledge is likely to be less useful to the hiring firm), and productivity in the hiring firm should hence not be affected by the tenure length of these workers.

The predictions of the unmeasured worker quality channel in relation to worker tenure depend upon what mechanism underlies the positive assortative matching between firms and workers. If productive firms are providing better quality training to their workers (making them more productive at future employers), we would expect to see larger productivity gains for longer tenured workers. However, if productive firms are simply better at screening workers (making the previous employer a signal for the worker's innate productivity), then their tenure at the previous employer is less likely to have a dramatic effect on the productivity gains to the hiring firm.

To explore these ideas further, the productivity gaps and hiring intensities in the baseline model are sub-divided into workers with long tenure, and workers with short tenure. More formally, the change in the firm's knowledge in the baseline model now takes on the form

$$\begin{aligned}\text{Exposure}_{i,t} \quad = \quad & \sum_{\text{tenure} \in \left\{\substack{\text{long,} \\ \text{short}}\right\}} \beta_{M,\text{tenure}} \frac{\sum\limits_{n \in \mathcal{N}^M_{j,t-1}} \mathbb{D}_{\text{tenure}}(n)[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\ & + \sum_{\text{tenure} \in \left\{\substack{\text{long,} \\ \text{short}}\right\}} \beta_{L,\text{tenure}} \frac{\sum\limits_{n \in \mathcal{N}^L_{i,t-1}} \mathbb{D}_{\text{tenure}}(n)[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\ & + \sum_{s \in \mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}, \qquad (10)\end{aligned}$$

where '$\text{tenure} = \text{long}$' denotes workers with long tenure, '$\text{tenure} = \text{short}$' denotes workers with short tenure, $\mathbb{D}_{\text{tenure}}(n)$ is a dummy variable that takes on the value 1 if worker n has tenure length given by 'tenure' in their previous main job, and 0 otherwise. Therefore $\beta_{M,\text{long}}$ denotes the effect of the productivity gap associated with hires of workers from more productive firms who have long tenure at that firm. The threshold of 12 months is used to define short and long tenured workers.

One potential issue with the analysis of tenure described above is that it does not control for time spent at the hiring firm. If workers with long tenure at their previous main job are not spending enough time at the hiring firm, they may be unable to have much of an effect on the hiring firm's productivity. So as a further extension to the analysis, a second definition of 'long tenure workers' is also considered. In this alternative definition, a long tenured worker is one who has had a tenure of at least 12 months in their previous main job before being hired, and who also spend at least 12 months employed in the hiring firm (all new hires who fail to meet both of these conditions are grouped together into the short tenured group). Imposing this extra tenure requirement on the time spent at the hiring firm ensures that workers hired in the previous period remain employed at the firm long enough to influence the firm's production in the current period (since the productivity gap is based on hires in year $t-1$, and the dependent variable is productivity growth in year t).

For each productivity measure, Table 9 presents three columns of results. The first column is the baseline regression results seen previously. The second column decomposes the productivity gaps and hire intensities based on the worker's length of tenure at their previous firm. The third column uses the alternative definition of long tenured workers based on their time at both the previous and the hiring firms.

Table 9 — Effects of considering worker tenure

	Value-added			Cobb-Douglas			Trans-log		
	Baseline	Tenure at:		Baseline	Tenure at:		Baseline	Tenure at:	
		Sending	Sending & hiring		Sending	Sending & hiring		Sending	Sending & hiring
Prod. gap, hires from (β):									
More prod. firms	0.480***			0.271***			0.354***		
	(0.098)			(0.065)			(0.068)		
With long tenure		0.375***	0.754***		0.331***	0.316*		0.325***	0.552**
		(0.138)	(0.280)		(0.109)	(0.190)		(0.116)	(0.229)
With short tenure		0.550***	0.419***		0.216***	0.254***		0.343***	0.292***
		(0.155)	(0.115)		(0.075)	(0.075)		(0.091)	(0.078)
Less prod. firms	0.153***			0.374***			0.374***		
	(0.030)			(0.054)			(0.056)		
With long tenure		0.187***	0.255***		0.599***	0.766***		0.569***	0.679***
		(0.053)	(0.066)		(0.114)	(0.161)		(0.087)	(0.130)
With short tenure		0.116**	0.099**		0.232***	0.288***		0.226***	0.281***
		(0.045)	(0.045)		(0.087)	(0.059)		(0.086)	(0.068)
Hire intensity (λ):									
More prod. firms	-0.200***			-0.012			-0.037*		
	(0.057)			(0.028)			(0.021)		
With long tenure		-0.142*	-0.247*		-0.022	0.010		-0.024	-0.053
		(0.073)	(0.131)		(0.041)	(0.060)		(0.032)	(0.058)
With short tenure		-0.242***	-0.190***		-0.005	-0.018		-0.041	-0.031
		(0.085)	(0.068)		(0.034)	(0.035)		(0.028)	(0.025)
Less prod. firms	-0.117***			0.047*			0.004		
	(0.027)			(0.026)			(0.019)		
With long tenure		-0.123***	-0.140**		0.067*	0.120**		0.041	0.072
		(0.043)	(0.056)		(0.041)	(0.057)		(0.030)	(0.048)
With short tenure		-0.111***	-0.125***		0.048	0.030		-0.023	-0.019
		(0.037)	(0.035)		(0.040)	(0.031)		(0.026)	(0.021)
Parameter tests:									
$\Pr(\beta_{M,\text{long}} = \beta_{L,\text{long}})$		0.200	0.085		0.094	0.074		0.097	0.630
$\Pr(\beta_{M,\text{short}} = \beta_{L,\text{short}})$		0.006	0.007		0.891	0.724		0.344	0.916
$\Pr(\beta_{M,\text{long}} = \beta_{M,\text{short}})$		0.445	0.297		0.421	0.773		0.915	0.316
$\Pr(\beta_{L,\text{long}} = \beta_{L,\text{short}})$		0.350	0.092		0.030	0.008		0.013	0.016
$\Pr(\lambda_{M,\text{long}} = \lambda_{L,\text{long}})$		0.835	0.449		0.133	0.185		0.149	0.094
$\Pr(\lambda_{M,\text{short}} = \lambda_{L,\text{short}})$		0.191	0.449		0.331	0.321		0.651	0.735
$\Pr(\lambda_{M,\text{long}} = \lambda_{M,\text{short}})$		0.383	0.713		0.753	0.702		0.705	0.750
$\Pr(\lambda_{L,\text{long}} = \lambda_{L,\text{short}})$		0.841	0.841		0.754	0.190		0.134	0.105
Obs.	37269	37269	37269	28260	28260	28260	38037	38037	38037

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$, where the measure of productivity differs by column. The cut off length for distinguishing between long and short tenure is equal to 12 months of previous employment at the respective firm. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Turning first to the definition of long tenured workers based solely on tenure length at their previous employer (the sending firm), for all of the productivity measures in Table 9, the point estimates of the coefficients related to both the productivity gaps from more productive firms and also the coefficients on the hiring intensities are broadly similar across short and long term workers). However, the coefficients on the productivity gaps related to hires from less productive firms do show some systematic differences from the baseline across all productivity measures (although not significantly different). For all productivity measures, the coefficient on the productivity gaps related to hires from less productive firms is larger for longer tenured workers than short tenured workers.

When the 12-month tenure requirement for long tenured workers is imposed at both the sending and hiring firm, the coefficient on the productivity gap for long tenured hires from more productive firms rises from 0.375 to 0.754 when using value-added per worker as the firm's productivity measure.[31] For hires from less productive firms, the increase in the productivity gap coefficient related to long tenured hires is relatively small (from 0.187 to 0.255). When MFP is used, there is a general increase in the coefficient on the productivity gap for long tenured workers hired from less productive firms (an increase of 0.167 for Cobb-Douglas and 0.11 for trans-log), and in the case of trans-log productivity, we also see an increase in the productivity gap coefficient related to long tenured workers from more productive firms (from 0.325 to 0.552). The remaining parameters in the model are generally not affected by the distinction between long and short tenured workers.

From the perspective of the knowledge spillover channel in the value-added data, the data suggests longer tenure at the sending firm is actually related to less, not more, gains in the productivity gap from more productivity firms. And in the case of hires from less productive firms, longer tenure at the sending firm is actually correlated with lower productivity growth at the hiring firm. Both of these contradict the predictions of the knowledge spillover channel (where longer tenure at the sending firm should be beneficial to the hiring firm). When tenure at both the sending and hiring firms are considered, we do see the expected larger coefficient on longer tenured hires from more productive firms relative to shorter tenured workers. However, the coefficient on the productivity gap of longer tenured workers from less productive firms still remains larger than for shorter tenured workers.

The unmeasured worker quality channel would suggest we might see longer tenured workers at the sending firm having more of a positive influence on the hiring firm's productivity when workers receive some form of on-the-job training. However, in the MFP results we see little difference between the coefficients related to long and short tenured workers from more productive firms. In the case of workers hired from less productive firms, the productivity gap coefficient related to longer tenured workers suggests that for a given difference in productivity between the sending and hiring firms, hiring workers with longer tenure at the sending firm results in lower (not higher) productivity growth.

Table 10 repeats the above decomposition into long-tenured and short-tenured workers for the model estimated using the capital-labour ratio rather than productivity. The premium in the input intensity gap associated with hiring workers from more productive firms is driven predominantly by workers with more than 12 months tenure at their previous main employer.

The results for the capital-labour ratio are in line with what one would expect to see if there is a knowledge spillover from more input intensive firms. Having a longer tenure at more input-intensive firms would give the workers an opportunity to acquire more knowledge/experience with these more input-intensive production methods, and hence workers from more productive firms should be able to transmit more knowledge to the hiring firm relative to a worker with less experience. Tenure does not seem to affect the input-intensity gains much for hires from less input intensive firms, who are less likely to transmit new knowledge.

Overall, the relationship between worker tenure and the productivity gains from the productivity gaps do not support any of the channels considered. However, when looking at the capital-labour ratio, we do find support for tenure benefiting the input-intensity gains, and this result is consistent with the predictions of the knowledge spillover channel.

[31] With the way long-tenured workers are defined in this second set of results, the most relevant comparison of parameters to make is between long tenured workers under both definitions. This illustrates the effect of tenure at the hiring firm for these workers.

Table 10 — Effects of considering worker tenure — capital-labour ratio

	Capital-Labor		
	Baseline	Tenure at:	
		Sending	Sending & hiring
Capital intensity gap, hires from (β):			
More capital-intensive firms	0.047***		
	(0.017)		
With long tenure		0.138***	0.376***
		(0.038)	(0.095)
With short tenure		-0.011	0.004
		(0.033)	(0.019)
Less capital-intensive firms	0.021		
	(0.024)		
With long tenure		0.077*	0.110*
		(0.042)	(0.059)
With short tenure		0.071	0.004
		(0.050)	(0.028)
Hire intensity (λ):			
More capital-intensive firms	0.071**		
	(0.031)		
With long tenure		0.031	-0.187**
		(0.054)	(0.090)
With short tenure		0.071	0.101***
		(0.050)	(0.038)
Less capital-intensive firms	-0.182***		
	(0.035)		
With long tenure		-0.138***	-0.239***
		(0.053)	(0.069)
With short tenure		-0.211***	-0.150***
		(0.058)	(0.045)
Parameter tests:			
$\Pr(\beta_{M,\text{long}} = \beta_{L,\text{long}})$		0.273	0.018
$\Pr(\beta_{M,\text{short}} = \beta_{L,\text{short}})$		0.990	0.987
$\Pr(\beta_{M,\text{long}} = \beta_{M,\text{short}})$		0.014	0.000
$\Pr(\beta_{L,\text{long}} = \beta_{L,\text{short}})$		0.106	0.113
$\Pr(\lambda_{M,\text{long}} = \lambda_{L,\text{long}})$		0.028	0.656
$\Pr(\lambda_{M,\text{short}} = \lambda_{L,\text{short}})$		0.000	0.000
$\Pr(\lambda_{M,\text{long}} = \lambda_{M,\text{short}})$		0.637	0.006
$\Pr(\lambda_{L,\text{long}} = \lambda_{L,\text{short}})$		0.386	0.315
Obs.	28260	28260	28260

Notes: The dependent variable in the regressions is the change in log capital-labour ratio. The cut off length for distinguishing between long and short tenure is equal to 12 months of previous employment at the respective firm. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln(K_{i,j,t-1}/L_{i,j,t-1})$ is instrumented for using $\ln(K_{i,j,t-2}/L_{i,j,t-2})$ in response to the presence of Nickell bias. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2.3 Workers' skill complementarity

The results of the baseline regressions using MFP measures are broadly in line with the predictions made by the unmeasured worker quality channel. Another prediction from this channel that can be tested is whether or not the coefficients on the productivity gaps vary with measured worker quality. Because the baseline model already controls for measured worker quality (through the regressor $\Delta Q_{i,t}$), the productivity gap relates to the potential productivity gains/losses to the hiring firm from the component of worker skill that is not already captured by the measure of worker quality derived from the worker's wage data. As a result, the unmeasured worker quality channel predicts that the effect of the productivity gap should not vary with observed worker skill.

On the other hand, the productive knowledge spillover channel does predict that we may see a relationship between the measured quality of new hires and the effect of the productivity gap on the hiring firm's productivity. According to the knowledge spillover channel, workers who are skillful enough to acquire high levels of human capital (worker quality) are also likely to be able to acquire more knowledge as to how their employer operates. Alternatively more skillful workers may have greater autonomy in the reach or scope of their job within the hiring firm. Hence they may be more capable of implementing new productivity ideas in the hiring firm. Either way, more skillful workers may be able to have a large effect on productivity gains when compared to less skillful workers.

Table 11 reports the regression results from investigating the relationship between worker skill and the amount of productivity knowledge transferred to the hiring firm. The productivity gap and hire intensities related to hires from more and less productive firms are further divided into new variables based upon the new hire's measure of worker quality. For simplicity the new groupings are based on whether the worker's measured quality is in the top, middle, or bottom third of the economy-wide distribution of worker quality. More formally the change in the hiring firm's stock of productive knowledge is modelled as:

$$\begin{aligned}
\text{Exposure}_{i,t} \quad = & \sum_{\text{skill}\in\{\text{low,med,high}\}} \beta_{M,\text{skill}} \frac{\sum_{n\in\mathcal{N}^{M}_{j,t-1}} \mathbb{D}_{\text{skill}}(n)[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\
& + \sum_{\text{skill}\in\{\text{low,med,high}\}} \beta_{L,\text{skill}} \frac{\sum_{n\in\mathcal{N}^{L}_{i,t-1}} \mathbb{D}_{\text{skill}}(n)[\ln(A_{n,\tau(n)}) - \ln(A_{i,t-1})]}{L_{i,t-1}} \\
& + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}, \qquad (11)
\end{aligned}$$

where '$\text{skill} = \text{low}$' denotes a worker skill in the bottom third of the distribution of worker quality, '$\text{skill} = \text{med}$' denotes a worker skill in the middle third, and '$\text{skill} = \text{high}$' denotes a worker skill in the top third. $\mathbb{D}_{\text{skill}}(n)$ is a dummy variable that takes on the value 1 if worker n is in the skill third of the distribution of worker quality.

For all three productivity measures in Table 11, the productivity gap associated with hiring low skilled workers from more productive firms has a smaller influence on the hiring firm's productivity growth than the productivity gaps associated with hiring medium and high skilled workers from more productive firms (although the difference is generally not statistically different). For both the value-added and trans-log MFP measures of productivity, the coefficient for the productivity gap associated with low skilled hires from more productive firms is around half that of the coefficient for other skill groups. So for example, if a firm with a hiring intensity from more productive firms of 10 percent was hiring low skilled workers, raising the average productivity of the firms these workers were sourced from by one percent would be associated with a 0.38 percentage point increase in labour productivity on average. While if the firm instead hired medium or high skilled workers, raising the average productivity of the firms these workers were sourced from by one percent would be associated with around a 0.7 percentage point increase in firm productivity growth.

Table 11 — Worker flows by worker skill level

	Value-added		Cobb-Douglas		Trans-log	
	Baseline	**By skill Group**	**Baseline**	**By skill Group**	**Baseline**	**By skill Group**
Productivity gap, hires from (β):						
More prod. firms	0.480***		0.271***		0.354***	
	(0.098)		(0.065)		(0.068)	
Low skilled		0.380**		0.255		0.225
		(0.179)		(0.170)		(0.147)
Medium skilled		0.701**		0.348**		0.673***
		(0.273)		(0.140)		(0.164)
High skilled		0.700***		0.310**		0.466***
		(0.179)		(0.142)		(0.157)
Less prod. firms	0.153***		0.374***		0.374***	
	(0.030)		(0.054)		(0.056)	
Low skilled		0.097		0.477**		0.427**
		(0.094)		(0.204)		(0.167)
Medium skilled		0.134		0.497**		0.517***
		(0.109)		(0.232)		(0.176)
High skilled		0.159*		0.444***		0.359**
		(0.085)		(0.170)		(0.159)
Hire intensity (λ):						
More prod. firms	-0.200***		-0.012		-0.037*	
	(0.057)		(0.028)		(0.021)	
Less prod. firms	-0.117***		0.047*		0.004	
	(0.027)		(0.026)		(0.019)	
Low skilled		-0.083		0.055		-0.005
		(0.058)		(0.065)		(0.039)
Medium skilled		-0.210**		0.001		-0.040
		(0.089)		(0.062)		(0.038)
High skilled		-0.268***		0.040		-0.037
		(0.072)		(0.057)		(0.037)
Unknown skill		0.702		0.262		0.480
		(0.920)		(0.501)		(0.349)
Parameter tests:						
$\Pr(\beta_{M,low} = \beta_{L,low})$		0.241		0.496		0.457
$\Pr(\beta_{M,med} = \beta_{L,med})$		0.105		0.641		0.580
$\Pr(\beta_{M,high} = \beta_{L,high})$		0.022		0.608		0.682
$\Pr(\beta_{M,low} = \beta_{M,med} = \beta_{M,high})$		0.408		0.907		0.130
$\Pr(\beta_{L,low} = \beta_{L,med} = \beta_{L,high})$		0.909		0.985		0.834
Obs.	37269	37269	28260	28260	38037	38037

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$, where the measure of productivity differs by column. Low, medium, and high skill denotes which third of distribution of worker quality an individual is in relative to the population at the time of hiring. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The coefficients related to the productivity gap for hires from less productive firms are similar in magnitude across all skill levels for each of the productivity measures, and are not statistically different from each another. The expected gain in productivity growth when improving the productivity of the less productive firms workers were sourced from would not differ across the various worker quality categories.

Taken at face value, the implications of these results do not line up directly with the predictions from either the knowledge spillover or unmeasured worker quality channels. In terms of the knowledge spillover channel, while we do see a larger coefficient on the productivity gap from more productive firms when comparing medium to low skilled workers, we do not see the same pattern when comparing medium to high skilled workers. In addition, this relationship between worker skill and the productivity gap effect is not isolated to labour productivity, where we have seen previous support for the knowledge spillover channel, but also affects the MFP results in which we have not seen previous support for a knowledge spillover channel.

In terms of the unmeasured worker quality channel, the baseline results showed support for unmeasured worker quality influencing firm MFP growth. However, the results in Table 11 suggest that the productivity gap for low skilled workers has a different effect from the productivity gaps of medium and high skilled workers, contradicting the predictions of the unmeasured worker quality channel.

One possible explanation for the contradictions found above is that low skilled labour is utilised differently in the production process when compared to medium and high skilled labour (e.g. only low skill workers perform manual labour jobs while higher skilled labour is used to perform other tasks). The measures of productivity so far assume that labour is a homogenous input into the production process. If low skilled labour is in effect utilised differently to medium and high skilled labour, the production function specifications used may not fully capture the distinction between low and other skilled labour inputs. This will affect the measures of productivity and hence the estimated productivity gains associated with hiring workers of different skill.

If we assume that low skilled workers are a different type of production input for the firm, the results above suggest that worker skill (the distinction between medium and high skill) does not affect the productivity gap for either MFP or labour productivity. This is consistent with the unmeasured worker quality channel. Furthermore, because the value-added and MFP results do not differ dramatically, this similarity also suggests that worker skill is not an important determinant of the productivity knowledge spillover seen in labour productivity results.

5.3 Robustness

The regression analysis conducted so far has only identified correlations between the hiring of new workers and the subsequent productivity growth in the hiring firm. While these correlations are consistent with the predictions of a worker quality channel and knowledge spillover, the regressions alone do not imply causality. It is possible that the causality runs in the other direction, i.e. decisions at the firm, or other outside factors are inducing productivity shocks, which in turn drive the observed hiring patterns. The analysis in this section attempts to provide some control for causality within the model, and deal with other issues of robustness of the results.[32]

[32] Additional robustness checks are presented in the online appendix.

5.3.1 Reverse causality – Estimates of shocks

To properly control for the direction of causality would require either knowing the productivity shocks that the firm observes when making its hiring decisions or knowing the reason for each new hire. While this level of control is not possible in the data, several techniques have been developed in the literature that attempt to identify the productivity shocks the firm observes, but that are hidden to the econometrician. For example, Levinsohn and Petrin (2003) developed a model that assumes observing changes in the firm's choice of material inputs into the production function provides information on the productivity shocks observed by the firm. Using the technique they developed, it is possible to back out estimates of the productivity shocks the firm observes before choosing labour and capital inputs, allowing us to estimate the component of MFP excluding the productivity shocks observed by the firm, thereby avoiding the reverse causality.[33]

Table 12 compares the regression results found using the MFP measure from the Cobb-Douglas production function and that productivity measure found using the Levinsohn and Petrin (2003) technique. The Cobb-Douglas results are used as the point of comparison here as the Levinsohn and Petrin (2003) approach uses a Cobb-Douglas production function to estimate MFP.[34] In the Levinsohn and Petrin (2003) results, the coefficients on the productivity gap variable are slightly lower for both hires from more productive (0.211 vs 0.271) and less productive (0.213 vs 0.374) firms. While the difference in magnitudes between the coefficients on the productivity gaps for hires from more and less productive firms were not statistically significant in the Cobb-Douglas case, the two coefficients become more similar in size after controlling for the productivity shocks observed by the firm. This brings the results in line with those based on the trans-log productivity measure. As a result, after controlling for the Levinsohn and Petrin (2003) productivity shocks, the Cobb-Douglas model estimation results provide slightly stronger support in favour of the unmeasured worker quality channel.

The Levinsohn and Petrin (2003) results give us some confidence that reverse causality does not significantly drive the findings of this paper. However, it is not possible to definitively rule out further effects from reverse causality that we are unable to control for given the data available.

5.3.2 Reverse causality – Business Operations Survey

One approach that speaks to the direction of causality in the regression is to use data from the Business Operations Survey (BOS). Every second year, the Business Operations Survey, a nationally representative survey, includes an innovation module that asks firms about their innovation practices over the previous two years and the factors that contributed to this innovation. As noted in the introduction of this paper, in 2019 over half of the firms that reported innovating over the previous two years claimed that new workers were an important source of ideas for this innovation.

33 Another common approach in the literature is that developed by Olley and Pakes (1996). However, the necessary investment data is only collected in the data through the Annual Enterprise Survey (AES), which is only available for a subset of firms in the data. Therefore the approach of Levinsohn and Petrin (2003) is favored as it provides a larger sample size to work with.

34 The Stata function 'levpet' developed by Petrin, Poi, and Levinsohn (2004) is used to construct the Levinsohn-Petrin productivity measure.

Table 12 — Effect of controlling for unobserved productivity shocks

	Cobb-Douglas	Levinsohn-Petrin
Productivity gap, hires from (β):		
More prod. firms	0.271***	0.211***
	(0.065)	(0.037)
Less prod. firms	0.374***	0.213***
	(0.054)	(0.056)
Hire intensity (λ):		
More prod. firms	-0.012	0.021
	(0.028)	(0.025)
Less prod. firms	0.047*	-0.010
	(0.026)	(0.036)
$\Delta Q_{i,t}$ due to (γ):		
New hires	0.105*	0.122**
	(0.062)	(0.060)
Exiters	0.103*	0.120**
	(0.062)	(0.060)
Incumbents	0.110*	0.120**
	(0.062)	(0.059)
Parameter tests:		
$\Pr(\beta_M = \beta_L)$	0.217	0.983
$\Pr(\lambda_M = \lambda_L)$	0.145	0.501
Obs.	28260	38037

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$, where the measure of productivity differs by column. The Levinsohn-Petrin measure of productivity is derived using the method developed by Levinsohn and Petrin (2003). Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Assuming that the concept of innovation that responding businesses have in mind when completing the survey is correlated with productivity growth, a business' response to whether new workers are an important source of ideas for the innovation carried out provides a strong indicator for whether or not the firm's productivity growth has been exposed to knowledge spillover from the labour mobility channel.

To determine if the regression correlations found are a result of knowledge spillover, the model is re-estimated on the sub-samples of firms who say workers are, and are not, an important source of ideas for the innovation carried out by the firm. If the coefficients do not differ dramatically between the two groups, it is unlikely that knowledge spillover is driving the correlations observed in the regression results. However, if the correlations between productivity growth and the productivity gap from more productive firms is larger for the businesses who report that new workers were an important source of ideas, then this could be viewed as support for a causal interpretation of knowledge spillover.

Table 13 presents the regression results estimated on the sub-samples of firms in the data set that reported conducting some form of innovation over the proceeding two years, and responded to the question indicating whether or not new workers were an important source of ideas for the innovation carried out. Because the time period for this survey question is two years, the model has been adjusted such that one period in the model (t) corresponds to two years.

With regards to the multi-factor productivity measures, the coefficients on the productivity gaps are broadly similar between the two sub-sets of firms for both the Cobb-Douglas and Trans-log productivity measures. As with the baseline results before, there is no statistical difference between the coefficient for the productivity gap from more productive firms, and the productivity gap from the less productive firms. Because the early results in this paper were generally inconsistent with the idea of knowledge spillover related to multi-factor productivity, the fact we see no large differences between the two sub-sets of firms further supports the idea that knowledge spillover is not related to multi-factor productivity knowledge.

With regards to labour productivity (value-added per worker), table 13 shows that the coefficients on the productivity gaps are larger for businesses that report new workers were an important source of ideas for the innovation the business carried out. This suggests businesses who gained from knowledge spillover benefit more from an increase in the average productivity of the new worker's previous employer. This finding leads support to knowledge spillover through the labour mobility channel.

However, the results also suggest that not all of the labour productivity gains from raising the average productivity of the firms new workers are sourced from is driven by knowledge spillover through the labour mobility channel. Businesses that reported new workers were not an important source of ideas for the innovation carried out still benefit more from improving the average productivity of the more productive firms they hire from than improving the average productivity of the less productive firms. However, the magnitude of this benefit is smaller than that experienced by businesses who reported benefiting from the new ideas of workers. This suggests that at least some of the correlation observed in the regressions is a result of causality running in the direction of productivity changes in the firm driving the hiring practices.

Table 13 — Regression based on Business Operation Survey respondents

	Value-added		Cobb-Douglas		Trans-log	
New workers are a source of ideas:	**True**	**False**	**True**	**False**	**True**	**False**
Productivity gap, hires from (β):						
More prod. firms	0.709***	0.332***	0.311	0.492	0.539***	0.510
	(0.199)	(0.113)	(0.251)	(0.374)	(0.106)	(0.470)
Less prod. firms	0.225**	-0.078	0.123	0.567**	0.476**	0.471**
	(0.099)	(0.132)	(0.201)	(0.225)	(0.223)	(0.239)
Hire intensity (λ):						
More prod. firms	-0.413***	-0.000	-0.074	-0.147	-0.116***	-0.082
	(0.136)	(0.122)	(0.096)	(0.193)	(0.044)	(0.211)
Less prod. firms	-0.060	-0.210	-0.019	0.186*	0.090	0.098
	(0.099)	(0.128)	(0.108)	(0.110)	(0.084)	(0.078)
Parameter tests:						
$\Pr(\beta_M = \beta_L)$	0.017	0.012	0.507	0.840	0.763	0.937
$\Pr(\lambda_M = \lambda_L)$	0.070	0.231	0.735	0.202	0.062	0.482
Obs.	1161	783	1170	795	1170	795

Notes: The columns True and False refer to the businesses response to the question in the BOS that asks if new workers (hired in the last two years) were an important source of ideas for the innovation that the firm carried out. Only firms who indicated they carried out innovation are included in this sub-sample. One period in this model corresponds to two years in the data. The dependent variable is $\Delta \ln A_{i,j,t}$. The second and third column of each productivity measures adds to the baseline model the average productivity difference, and the squared productivity gap respectively. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6. Conclusion

The analysis carried out within this paper shows that when hiring new workers, the productivity of a worker's previous main employer is significantly correlated with the future productivity growth of the hiring firm. The strength of this correlation varies with the measure of firm productivity used, whether the firm hires from more or less productive firms, and with some characteristics of the new workers themselves.

When firm productivity is measured in terms of labour productivity (value-added per worker), the productivity gain associated with raising the average productivity of the firms that new workers are sourced from is, on average, large (small) if the hiring firm is sourcing its new workers from firms that were more (less) productive than the hiring firm. This 'premium' for hiring from more productive firms tend to be larger when the new hires are from the same industry as the hiring firm, the new hires have spent more than one year at both their previous firm and the hiring firm, and the new hires have a medium to high level of worker quality. This premium is also observed when measures of input intensity (the capital-labour ratio) is used instead of productivity.

In terms of multi-factor productivity, the productivity gain associated with improving the average productivity of firms that new workers are sourced from is independent of whether the increase in average productivity is driven by improvements to the productivity at the top or bottom ends of the distribution of source firms. Extensions to the baseline regression reveal that the magnitude of these gains are not dramatically affected by the characteristics mentioned above.

While these regression based correlations do not imply causality, it is still interesting to compare these findings to the predictions made by different models of how new hires influence firm productivity. The multi-factor productivity results are consistent with predictions of a worker quality/screening channel where more productive firms are either better at screening good quality workers or provide them with better training (creating positive assortative matching). Because the productivity of a worker's previous employer acts as a signal of worker quality, such a model would predict that the coefficients on the productivity gaps for hires from both more and less productive firms should be positive, and equal. In terms of the labour productivity results, the premium in the coefficient on the productivity gap for hires from more productive firms seen in the value-added productivity measure is consistent with the knowledge spillover channel. This channel predicts that workers from more productive firms are able to transmit new, better productivity ideas to the hiring firm. The fact that we see this relationship in the labour productivity measure, and the capital-labour ratio, but not the MFP data, would suggest the knowledge spillover is related to knowledge about production technology (more capital intensive production methods) not MFP (how to utilize the firm's current inputs more efficiently).

Although with the data that is available it is not possible to say definitively that it is the knowledge of new workers driving productivity growth in the hiring firms, the regressions results appear to be robust to further disaggregation of the productivity gap as well as various attempts to control for the direction of causality. This suggests that the empirical findings are at least consistent with hiring firms benefiting from the knowledge of new hires through both the worker quality and a knowledge spillover channels.

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