Firm Productivity Growth and its Relationship to the Knowledge of New Workers*

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November 27, 2017

Abstract

Using linked employer-employee data, productivity growth at a firm is related to the firm's exposure to outside knowledge, proxied by the difference between the hiring firm's productivity and the productivity of the new worker's previous employer. The estimated relationship is compared to the predictions implied by both the knowledge spillover and worker quality channels. While not a causal relationship, the multi-factor productivity results are consistent with the predictions of a worker quality channel in which positive assortative matching between workers and firms acts as a signal of the unmeasured worker quality that will benefit the hiring firm. When firm productivity is measured in terms of labor productivity, support is also found for the knowledge spillovers occurring from more to less productive firms through the labor mobility channel. Further investigation suggests that this knowledge spillover pertains to production technology knowledge, allowing the firm to operate at higher levels of capital intensity, and not multi-factor productivity knowledge, that would allow the firm to operate its current inputs more efficiently.

*The views expressed in this paper are those of the authors and do not necessarily reflect the views of the New Zealand Treasury, Statistics New Zealand, or the Ministry of Business, Innovation and Employment. The authors are grateful to Dave Maré and staff at the New Zealand Treasury for their comments on earlier drafts of this work. Michael Kirker would also like to thank Tim Ng and Peter Gardiner for their support and accommodation during his time at the Treasury.

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Disclaimer

The results in this paper are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics New Zealand.

The opinions, findings, recommendations, and conclusions expressed in this paper are those of the author(s), not Statistics NZ, the Treasury, or the Ministry of Business, Innovation and Employment.

Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this paper have been confidentialised to protect these groups from identification.

Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.

The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes.

Any person who has had access to the unit record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

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.

This paper aims to further the understanding of firm-level productivity in New Zealand by looking at the relationship between the skills and knowledge of new workers and the subsequent productivity growth experienced by the hiring firm. 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 2013 Business Operation Survey, 52 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 productivity growth within firms to the characteristics of new workers and the productivity level of the workers' previous employer. 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 main channels. The first is the productive knowledge spillover channel. According to this channel, through their participation in production, workers learn some knowledge used by a firm to operate at its given level of productivity. This knowledge can be valuable to less productive firms that could augment their productive knowledge with the new ideas. 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 labor 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, firm-level benefits from the reallocation of existing resources (in this case, workers' human capital) are inherently limited. In particular, firm-level productivity improvements due to improvements in 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, but in the absence of knowledge spillovers the impact on aggregate productivity is expected to be small.

The baseline results of the analysis 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 higher 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 firm productivity (which control for the use of capital and materials by the firm), raising the average productivity level of the less productive private-for-profit firms that new workers are sourced has the same expected benefit to the hiring firm's productivity growth as raising the average productivity level of the more productive private-for-profit 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 labor productivity (value-added per worker), increasing the average productivity level of the private-for-profit firms that workers are sourced from also leads to an expected increase in productivity growth at the hiring firm. However, unlike the MFP case, raising the average productivity level of the less productive private-for-profit 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 private-for-profit 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-labor 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 labor productivity growth, 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 labor 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 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.

Contents

1 Introduction

Innovation and productivity growth have always been important issues for policy makers. For at least the last few decades, productivity growth in New Zealand has underperformed relative to international benchmarks. This performance has been an ongoing concern for policy institutions (see Janssen and McLoughlin 2008 and de Serres et al. 2014 as examples). Therefore, improving our understanding of how productivity and innovation occur within the economy is an important step for improving the economic performance of New Zealand.

According to New Zealand firms, new staff are an important source of ideas for innovation. Every second year, 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 2013, 46 percent of responding businesses reported that they had implemented some form of innovation in the prior two years.[1] Of the businesses that reported carrying out some form of innovation, 52 percent reported that new staff were an important source of ideas for innovation. While firms may claim that new staff are an important source of ideas for innovation, the survey results do not capture the means by which new staff affect innovation, or if these innovation improvements lead to measurable productivity growth for the firms.

This paper aims to explore the relationship between new hires and measurable firm-level productivity growth with the aim of better understanding the channels through which firms benefit from the knowledge and ideas brought to the firm by new hires. The analysis uses a panel data set for New Zealand 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 labor 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 employed for 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

[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.

frequency, allowing for more precision in the timing of job starts/finishes. In addition, the employment data capture all employment spells, even those lasting less than a year.

This paper also 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 are likely to be correlated with its decision to hire from sources outside that scope. Without controlling for this, 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 labor 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, we focus on the intensive margin of hiring, the productivity of the new worker's previous firm, rather than 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 labor force.

When firm productivity is measured in terms of multi-factor productivity, raising the average productivity level of the private-for-profit firms that new workers are sourced from is associated with higher productivity growth in the hiring firm. 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 labor 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-division is larger when using value-added as the productivity measures than when using multi-factor productivity measures.

While causal relationships cannot be drawn from the data, the correlation patterns found in the data can be compared to the predictions made by the various theoretical channels through which new workers could benefit firm productivity. The overall pattern of correlations found in the analysis 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/total-factor productivity knowledge which would allow for the more efficient utilisation of existing inputs.

The remainder of the paper is structured as follows. Section 2 discusses in detail 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

In recent years, the availability of Linked Employer-Employee Data (LEED) around the world has improved. With greater access to data has come increased scrutiny of labor mobility as a driver of productivity growth at the firm level. One area in which the this type of data has been used in the literature is to examine the benefit of new workers to the hiring firm through the productive knowledge spillover channel — where workers transmit productive knowledge from their previous employer to the hiring firm.[3]

Typically in the literature, the share of new workers has been used as a proxy measure for a firm's exposure to new productive knowledge. 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 (2015) shows that the productivity of Italian manufacturing firms improves when hiring workers from high wage premium firms (a proxy for high productivity firms), and the benefit is larger when workers are from the same industry and/or have managerial or white-collar jobs, characteristics that are consistent with predictions of knowledge spillover from labor mobility.

Within the empirical literature on estimating knowledge spillover at the firm level, the analytical approach taken in this paper is most closely related to that by Stoyanov and Zubanov (2012). Rather than measuring the exposure to new knowledge based on the number of new hires, Stoyanov and Zubanov (2012) 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 hypothesis. Further support for the knowledge spillover channel comes from the finding that larger spillover coefficients are associated with worker characteristics expected to enhance workers' ability to transfer knowledge between firms (such as worker tenure and skill).

[3]Some of the previous literature has also used this channel to explore the transfer of knowledge from other countries through multinational enterprises. See Görg and Strobl (2005) and Balsvik (2011) as examples.

The analysis in this paper extends that of Stoyanov and Zubanov (2012) in a few key areas. Empirically, the data used in this paper provides coverage of all industries in the measured economy, not just the manufacturing sector. In addition, the employment data captures all job spells and is observed monthly, rather than annually. The structure of the analytical model also differs subtly from that used by Stoyanov and Zubanov (2012). The model used in this paper includes 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 labor mobility being a channel for productive knowledge spillover. In a recent working paper, Stockinger and Wolf (2016) apply an approach similar to that of Serafinelli (2015) and Stoyanov and Zubanov (2012) to look at knowledge spillover for labor movements between German firms in multiple industries. In their data, 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 inferior (lower-paying) establishments is associated with productivity gain. These findings are inconsistent with the story of labor mobility acting as a channel for productive knowledge spillover. Overall, their findings suggest the productivity gains associated with new hires are more consistent with an assortative matching process — where hires from inferior firms tend to bring in the more highly skilled workers in those firms, and hires from superior firms tend to attract the less skilled workers. 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 worker in New Zealand.

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 et al. (2014) find that a higher proportion of recent migrants (both immigrants and New Zealand expatriates returning from overseas) within the firms' workforce is correlated with a higher probability of self-reporting innovation in the BOS. In a somewhat related line of research, Sin et al. (2014) examine the link between employee characteristics and firms' exporting decisions, and between firms' exporting decisions and innovation in the BOS. Their findings suggest that hiring high skilled foreigners raises the probability that a firm exports, and exporting firms tend to be more innovative than non-exporting firms. While these findings only represent correlations, they are consistent with the causal story of foreign knowledge spillover through the international migration of labor.

The analysis carried out in this paper expands upon this previous New Zealand literature by considering all labor flows, not just those related to international migration. Even in a relatively open country like New Zealand, recent migrants represent only a small fraction of total labor flows each year. In addition, knowledge spillovers can occur between domestic firms as well as from international sources. Another way in which this paper expands upon the previous literature is by viewing firm-level innovation through the lens of measurable productivity (both labor and multi-factor productivity) rather than a binary self-reported survey response. This provides an alternative indication of the intensity and magnitude of innovation that is occurring within businesses.

3 Model

To investigate how firms benefit from the knowledge of new workers, this paper uses a modelling framework based on the approach taken by Stoyanov and Zubanov (2012). The 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

Productivity at the firm level can be measured using several different approaches. The analysis throughout this paper considers measures of productivity in terms of both labor productivity and multi-factor productivity (MFP).[4] Labor productivity has the advantages of being straightforward to compute, and it allows for direct comparisons on a like-for-like basis between firms in different industries and firms that employ different levels of inputs. In the analysis that follows, the labor productivity measure used 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 labor productivity for firm i in year t. Labor 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 labor input in FTE units.

Multi-factor productivity (MFP) on the other hand relaxes the assumption that output increases linearly with labor input, and measures a firm's productivity relative to a benchmark production function. 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 labor, capital, and materials respec-

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

tively.[5] Given information on the firm's level of output, inputs, and a functional form for the production function (e.g. Cobb-Douglas technology), one is able to use equation 2 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 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. The firm's exposure is assumed to be driving by an extensive margin — how much hiring of new workers the firm does — as well an intensive margin — how superior/inferior the knowledge of each worker is relative to the firm's current knowledge. 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 for the hiring firm's (firm i's) exposure to outside knowledge is given by

$$\text{Exposure}_{i,t} = \beta_{agg} \frac{\sum_{n \in \mathcal{N}_{i,t-1}} [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} + \sum_{s \in \mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}} \tag{3}$$

The first term in the right-had side in equation 3 is similar to what Stoyanov and Zubanov (2012) use in their model to measure knowledge spillover. They refer to the term as the 'productivity gap', a term that will also be adopted throughout this paper. $\mathcal{N}_{i,t-1}$ 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. The hiring firm's exposure to new knowledge from worker n depends upon the difference between the productivity of the worker's previous employer just prior to their departure, $\ln(A_{n,\tau-\delta})$ (where the worker left firm n at time τ), and the hiring firm's productivity just prior to hiring the new worker, $\ln(A_{i,t-1-\delta})$, where δ is some small measure of time.

The new knowledge from each new worker is summed over all hires and normalized by the size of the firm's labor force, $L_{i,t-1}$. Thus a firm will have a greater exposure to new knowledge ideas when (i) hiring a greater number of workers from more productive firms, or (ii) sourcing a given number of workers from even more productive firms.[6]

[5] 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 labor productivity or MFP.

[6] An equivalent way to write this productivity gap term is

$$\frac{\sum_{n \in \mathcal{N}_{i,t}} [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-\delta})]}{L_{i,t}} = \frac{\sum_{n \in \mathcal{N}_{i,t}} [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-\delta})]}{H_{i,t}} \frac{H_{i,t}}{L_{i,t}}$$

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 labor market (and hence have no previous employer), or may come from firms for which productivity cannot be measured in the data (e.g. 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. These hiring can then be grouped together into various sources outside the scope of analysis. The second term on the right hand side of equation 3 uses the number of hires from these different groups as an attempt to control for the knowledge spillover from new workers for which the previous employer's productivity cannot be measured. Throughout this paper, this will be referred to as the hiring intensity for the various sources.

More formally the second term on the right-hand side can be described as follows: 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 labor force size (the hiring intensity from source s). 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 3 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.

For the empirical work to follow, the following sources of new hires ($\mathcal{S}$) are used: (i) new workers for whom we have not observed any work history (e.g. new college 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); (iv) hires from private-for-profit firms that are within the scope of analysis but are missing some of the data required

where $H_{i,t}$ is the number of new hires made by the firm. In this specification, the knowledge gap represents the productivity difference between the hiring firm and the average source firm, multiplied by the share of new hires in the firm's labor force.

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

One limitation of the modelling approach adopted here is that it does not allow for the systematic depreciation of productive knowledge. 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.

3.2.1 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 give in equation 3, the model for most of the analysis will use separate productivity gaps for hires from *more* and *less* productive firms:

$$\begin{aligned}
\text{Exposure}_{i,t} &= \beta_M \frac{\sum_{n \in \mathcal{N}_j,t-1} \mathbb{D}_n [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
&\quad + \beta_L \frac{\sum_{n \in \mathcal{N}_i,t-1} (1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
&\quad + \sum_{s \in \mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}} \qquad (4)
\end{aligned}$$

where $\mathbb{D}_n$ is a dummy variable that takes on the value one when $\ln(A_{n,\tau-\delta}) \geq \ln(A_{i,t-\delta})$ (i.e. the productivity gap is positive for individual hire n). It is important to note that the sum of the productivity differences in the first term of equation 4 is always positive (since $\mathbb{D}_n$ selects only the cases where $\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-\delta}) > 0$), and the second summation is always negative.

3.3 Relationship between productivity growth and exposure

Having established how a firm's exposure to outside knowledge through labor mobility is defined, we now turn to modelling to relationship between productivity growth and the firm's exposure.

The key equation to be estimated by the analysis is given by the following first-difference representation of a dynamic panel model

$$\begin{aligned}\Delta \ln A_{i,j,t} &= \text{Exposure}_{i,t} + \gamma \Delta Q_{i,t} + \delta \Delta \text{ExTurn}_{i,t} + \sum_{l=1}^{L} \alpha_{A,l} \Delta \ln A_{i,j,t-l} \\ &\quad + \theta_{j,t} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where $\Delta \ln A_{i,j,t}$ is the change in log productivity for firm i, in industry j, at time t, $\Delta Q_{i,t}$ is the change in the average (measurable) worker quality in the firm, $\text{ExTurn}_{i,t}$ 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.

In equation 5, the firm's exposure to outside knowledge through labor mobility is related to the change in the hiring firm's productivity (or productivity growth) as a firm's productivity level is likely to depend upon the stock of productive knowledge within the firm. Greater exposure to outside knowledge allows new ideas to enter the firm augmenting the stock of knowledge, leading to productivity growth.

The remaining terms in equation 5 are additional controls. One important driver of a firm's productivity is the quality of the firm's work force. In general, measures of labor productivity and MFP only control for the quantity of labor, not the quality. As a result, fluctuations in the quality of the workers will appear as fluctuations in the firm's productivity level. Conceptually, new workers will affect the firm's productivity both through exposure to new knowledge, as well as by affecting the quality of the work force. In reality, we are not able to perfectly measure the quality of workers, and hence the change in quality due to the arrival of new workers. We therefore distinguish between measured worker quality ($Q_{i,t}$) and aspects of unmeasured quality which may be related to the productivity of the worker's previous employer (eg, due to more productive firms proving better training to workers). The component of worker quality that is unmeasured may appear as fluctuations in $\text{Exposure}_{i,t}$. However, we implicitly assume that any unmeasured worker quality component is orthogonal to the residual in the regression, and hence will either come through $\text{Exposure}_{i,t}$ or $Q_{i,t}$.

Excess labor 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 included as a control because labor turnover can be disruptive to a firm when a significant amount of resources are needed to replace workers and/or train up new workers. Hence when labor turnover is high, these costs will lead to lower levels of output, and this will manifest in lower measured firm productivity.[7]

The firm's past productivity performance can also affect today's productivity through influencing the firm's investment and hiring decisions made both today and in the past. The inclusion of productivity lags in equation 5 aims to capture and control for the dynamics of productivity over time. 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

[7]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 labor turnover.

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 control for some of the bias. This is because $\ln A_{i,t-2}$ is a natural instrument for $\Delta \ln A_{i,j,t-1}$. 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 in this paper. These approaches nest the first-difference approach described above, and expand the list of instruments available for use by including multiple lags of the past levels and differences of the dependent variable (in this case MFP). Results using a wider set of instruments are briefly discussed in the results section (see section 5.3).

As mentioned previously, equation 3 makes the implicit assumption that the new knowledge brought to the firm by new hires takes one period to implement (i.e. the productivity gap from hires in period $t-1$ influences productivity in period t). From a theoretical point of view, the ideas and knowledge of new workers cannot be implemented immediately upon their arrival. Either it will take some time for the firm to adjust their current production method to use the new knowledge, or it will take time for the new staff members to teach the new ideas and knowledge to other staff. From a practical point of view, because the hiring firm's own productivity is used to construct the productivity gap variable in the first term of equation 3, having the stock of productive knowledge influenced by hires in the current period will result in an endogeneity issue as the dependent variable $\ln(A_{i,j,t})$ would appear on both sides of the main regression equation.

However, the model given by equations 5 still allows new workers to influence productivity in the period in which they are hired through their influence on the average quality of the firm's labor force ($\Delta Q_{i,t}$). This is because workers are assumed to be able to exploit their innate skill and knowledge immediately in whatever tasks they perform.[8]

3.3.1 MFP and measuring the productivity gap

As discussed by Fabling and Maré (2015b), one of the issues with using an MFP measure of a firm's productivity is that MFP is measured relative to the average productivity in the industry. Therefore, it is not possible to directly compare the level of MFP between firms in different industries. This has important implications for the calculation of the productivity

[8]One limitation of the modelling approach taken here is that if the productivity gaps are in fact proxies for unmeasured worker quality (one of the channels which is considered, and discussed below), this implies that the worker's unmeasured quality does not have a contemptuous effect of productivity growth, while measured quality does. Given that the dependent variable (productivity of the hiring firm) is used to construct measures of the productivity gap, we do not see an obvious approach to dealing with this issue. However, a priori, the unmeasured worker quality of workers hired in period $t-1$ is still expected to influence productivity growth in period t as workers are generally hired throughout the year, not just at the start of each year.

gap variable used in equations 3 and 4 as a proxy for exposure to new productive knowledge. When the hiring firm hires a new worker with previous experience in a different industry, the productivity gap measure will exclude the difference between the average level of productivity between the two industries.

Whether using MFP as the measure of firm productivity means that the productivity gap is a misleading proxy of the hiring firm's exposure to new knowledge depends upon how applicable knowledge is between industries. For example, consider the extreme case when all knowledge is industry specific. In this case, new hires from other industries should not contribute to the hiring firm's stock of productive knowledge. However, the productivity gap constructed using MFP will include the productivity differences from hires from other industries, biasing the estimated coefficient towards zero.

The productivity gap will also have some bias when all productive knowledge is able to be utilized by firms in other industries. For example productivity may be higher in one industry than another because of a higher adoption rate of some superior business practices that can be utilized by all firms. In this case, the productivity gap constructed using an MFP measure will correctly capture the part of the productivity difference that make the hiring firm and the worker's previous employing firm more or less productive relative to their own industry, but fail to capture the difference in average productivity between the two industries.

However, the productivity gap computed using an MFP measure is not necessarily a biased proxy. This will be the case when the knowledge that creates differences in average productivity between industries cannot be utilized by the hiring firm, but the part of the a firm's productivity that makes the worker's previous employer a highly productive firm in its own industry can. For example, if the hiring firm is unable to utilize the types of capital that makes the other industry more productive on average, but it is able to utilize the superior management practices that made the new worker's previous employer highly productive within its own industry.

Whether a bias exists, and if so, what effect is has upon the results is an empirical issue that must be addressed. Appendix A.1 directly examines this issue by comparing the estimation results for the model using labor productivity (value-added per worker), against the results of the model estimated using labor productivity data that has been demeaned by industry-year, as an indicator whether the implicit de-meaning inherent in MFP measures is likely to be important. As a preview of the results, the between-industry productivity differences do not appear to have a significant effect on the estimation results.

3.4 Theoretical predictions

The aim of this paper is to investigate through which channels firms benefit from the exposure to new knowledge brought to them by their new workers. The empirical analysis to follow will be compared to the predictions made by two main channels that have often been proposed in the literature. The first channel considered is the *knowledge spillover* channel, where workers transmit new ideas from their previous employer to the hiring firm. The second channel considered is an *unmeasured worker quality* channel wherein a worker's previous employer is a signal of unmeasured worker quality either due to more productive firms being generally better at screening employees or providing more on-the-job training. These channels 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 equations 4 and 5.

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	$\approx \beta_M$	

Notes: The parameter predictions are based upon the model utilizing the disaggregated change in the stock of knowledge (equation 4). β_M is coefficient related to the productivity gap for hires from more productive firms. β_L is coefficient related to the productivity gap for hires from less productive firms. λ_M and λ_L are the parameters related to the change in productivity related to the firm's hiring intensity (the number of hires normalized by firm size) of workers from more and less productive firms.

3.4.1 Knowledge spillover

Since seminal work by the likes of Romer (1986) and Lucas (1988), the spillover of knowledge between firms has become an important mechanism used by endogenous growth models to explain the existence of long-run economic growth. There are numerous ways in which firms interact with each other that could facilitate the spillover of knowledge. One of the ways knowledge spillover is often modelled within the literature is via labor mobility (see Glass and Saggi 2002 and Fosfuri et al. 1998 as examples). According to this channel, workers absorb some of the productive knowledge and ideas of their current employer while working on the job. As a result, when a firm hires a new worker with previous experience at another firm, it not only buys the worker's labor skill, but also some of the productive knowledge of the other firm. This new knowledge is then absorbed into the hiring firm, where other workers are able to learn from it. Through this process, good ideas can diffuse throughout the economy from a single source firm, leading to economy-wide economic growth.

If the productive knowledge spillover channel is present in the data, then when hiring from a more productive firm, the hiring firm should have higher productivity growth due to the inflow of superior productive knowledge. Assuming adjustment costs are low enough and hiring firms have sufficient capacity to absorb the new knowledge, this benefit should be larger when the difference between the productivity of the previous firm and the hiring firm is larger. In the context of the model this 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 that 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. $\beta_L \approx 0$.

One would also expect that some types of workers will be better than others at facilitating knowledge spillover. For example, workers who have had a longer tenure at their previous employer have had a greater opportunity to absorb the firm's knowledge, or more skillful workers may be in a better position to understand the particular elements within the firm that make it productive or better able to implement that knowledge in a new firm. Therefore, for a given productivity difference between the hiring firm and the worker's previous employer we would expect to see larger productivity gains associated with certain groups of hires, i.e. β_M should be larger for workers with longer tenure at their previous employer than for workers with shorter tenure.

There may be a number of factors that limit the spillover of productive knowledge. For example, at higher levels of productivity, worker quality or other factors may be more important in determining productivity than the stock of productive knowledge. Alternatively, firms may have limited capacities to absorb new knowledge — they may not be able to implement new knowledge that is significantly more sophisticated than their current knowledge. Such effects are likely to attenuate the relationship between the productivity gap and productivity growth in the hiring firm. Therefore, as a check to see if there are limits to knowledge spillover, section 5.3 includes an extension to the model in which additional transformations of the productivity gap are included in the model as an attempt to capture any non-linearities in the relationship between the productivity gap and the productivity growth at the hiring firm.

The model used in this paper implicitly assumes that all workers within a firm have equal access to the productive knowledge of the firm. In reality, workers in different departments may have access to very different pools of productive knowledge. If firms are able to observe these knowledge differences and target their hirings to select knowledge that is the most useful to them (rather than base their hiring decisions on the overall productivity of the other firm), the estimated relationship between the productivity gap and future productivity growth will be weak. Instead, we would expect to see the coefficients related to hiring intensity being positive as each new worker brings some new knowledge, irrespective of their previous firm's overall productivity level (i.e. $\lambda_s > 0$).

3.4.2 Signal of unmeasured worker quality

Equation 5 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, from a firm's perspective, there may be aspects of worker quality that are not captured by the worker's income. For example, labor market frictions and Nash-bargaining are common labor market model features that result in a wedge between a worker's marginal product of labor and the wage they receive. Therefore, the measure of worker quality used for this paper's analysis may not fully capture the true (unobservable) worker quality from the perspective of the firm's productivity.

There are multiple ways in which one might expect a positive correlation between unobserved worker quality and 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).[9] Alternatively, productive firms might have better quality workers because they are better at producing quality workers. This could be a result of better on-the-job training or within-firm learning spillovers generated by interacting with the higher quality workforce already in the firm (see Nix 2015).[10]

If the previous employer's productivity provides a signal to the hiring firm regarding the unmeasured component of worker quality, then whether the previous employer's productivity was above or below the productivity of the hiring firm should be correlated with the change in unmeasured worker quality within the firm. Therefore, we would expect that hiring from more productive firms raises the unmeasured quality of labor on average, i.e. the coefficient on the productivity gap related to hires from more productive firms should be positive, $\beta_M > 0$. We would also expect that hiring from less productive firms should lower the unmeasured quality of labor on average, i.e. $\beta_L > 0$.

Furthermore, if firm productivity is being driven by the unmeasured worker quality, then the magnitudes of the coefficients β_M and β_L should be approximately equal. All else equal, a firm that hires two new workers, one with 10 percent higher unmeasured quality than the average incumbent worker, and one with 10 percent lower unmeasured quality, should have no overall change in the average unmeasured skill of the firm's workforce. Because firm productivity is assumed to be correlated with the unmeasured quality of its workers, in the absence of selection bias, the two new workers should be sourced from firms that are symmetrically more/less productive than the hiring firm.[11]

4 Data

The data for this paper is taken from two micro-level data sets maintained by Statistics New Zealand. Information regarding firms comes from the Longitudinal Business Database

[9] Most of the empirical work exploring assortative matching in the labor market has focused on using two-way fixed effects regressions on wage data. The results of this work have been mixed, but the results tend to show a slight negative, or zero, correlation between the firm and worker fixed effects (see Abowd et al. 2004 as an example). However, this work is based on decomposing wage data. It does not examine productivity data directly, and will therefore not account for the presence of any unmeasured worker quality.

[10] It is also possible we could see a negative benefit to the hiring firm's productivity if more productive firms are better at removing poor performing workers from their firm.

[11] The unmeasured worker quality channel may be sensitive to selection bias. The quality of workers who select to leave more and less productive firms may not be the same, weakening the correlation between the sending firm's productivity and the unmeasured quality of the worker. The summary statistics in 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). Therefore selection bias is unlikely to be a significant concern.

(LBD) which combines a range of survey and administrative data sources for all economically significant businesses in New Zealand since 1999.[12] Information on individual employees comes from the Integrated Data Infrastructure (IDI). The IDI 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 anonymized individual identification numbers.

The analysis in this paper is conducted at the firm-year level. In New Zealand the majority of businesses use a financial year ending in March to align with the tax year. However, this is not a strict requirement, and some particular industries follow a tax and financial year that ends in different calendar month. To ease the comparability between firms, each firm's financial year is mapped to the March-year with the most overlap to the firm's financial year. For simplicity, time is referred to by the March-year. Hence the year 2001 refers to the firm's financial year with the most overlap to the tax year ending March 2001.

The sample period for the analysis in this paper 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.[13] The scope of this analysis is restricted to private-for-profit businesses within the measured sector identified by Statistics New Zealand.[14] Only for these types of businesses do we believe that revenue and cost data will provide a suitable indicator for productivity.

The main variable of interest in this analysis is the productivity level of firms. Fabling and Maré (2015b) detail how to construct measures of Multi-Factor Productivity (MFP) for firms using the LBD data set. For the analysis conducted in this paper, we adopt their estimates of MFP based on both the Cobb-Douglas and trans-log production functions.[15]

[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 this and a detailed discussion of the LBD see Fabling and Sanderson (2016).

[13] For example, if a partnership decides to incorporate into a company, this would appear as two separate enterprise numbers in the LBD, but would be a single PENT, and hence a single firm in this analysis.

[14] 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".

[15] Fabling and Maré (2015b) also estimate a third specification based on the Cobb-Douglas with firm-specific fixed effects (where the fixed effect is assumed to be part of the firm's MFP). The results based on

Both of these production functions are estimated at the industry-year level, reflecting the fact that the survey and tax information on revenue and expenditures is only available at this frequency. The industry classification is grouped into 39 separate industries covering the measured sector.[16]

In addition to the MFP measures of productivity, we also consider a measure of labor productivity computed as the (real) value added per worker. The measures of real output, materials, and labor used here are taken from the same LBD sources as those used to compute the MFP measures of productivity.[17]

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 in this paper 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.[18]

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 and pin down the timing of these transitions so we are able to construct productivity gap measures.

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this measure did not differ dramatically from the results found using the standard Cobb-Douglas production function and are therefore not presented in the main body of this paper. Results for this other MFP measure are available in appendix B.2.

[16]The level of detail in classifying industries is close to that of level 3 of the ANZSIC06 New Zealand Standard Industrial Output Categories (NZSIOC). See appendix 1 of Fabling and Maré (2015b) for more details.

[17]Appendix C provides further summary statistic information on the firm-level data.

[18]As shown in table 23 of appendix C, 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 presented in this paper do not appear to be overly sensitive to the choice of minimum firm size.

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 labor flows in the economy in the measure of the productivity gap. The results of this paper do not differ much if the minimum firm size for the worker's previous employer is raised to ten.

4.2.1 Worker quality

The measure of average observed worker quality for each firm ($Q_{i,t}$) is computed as the average of the measured quality of each employee, weighted by their contribution of total full-time equivalent (FTE) labor for the firm. The measure of individual worker quality/human capital is constructed following the approach of Hyslop and Maré (2009) who utilize the two-way fixed effects regressions on wage data developed by Abowd et al. (1999). From updated estimates using the IDI (which has replaced the LEED data initially used by Hyslop and Maré 2009), the measure of worker 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.[19] As such, the worker quality captures observable demographic characteristics alongside a time-invariant estimate of a worker's ability. This time-invariant component captures a range of characteristics including occupation, education and skill, and relies on an assumption that workers are fairly compensated for the value they bring to their employers.

Unfortunately, the IDI does not have detailed information on hours worked for the majority of employees in the firm. Therefore the full-time equivalent (FTE) labour supply of each worker is estimated using the approach developed by Fabling and Maré (2015a). This approach uses information on the worker's monthly income to estimate their labor 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 labor input for some workers such as part-time workers who are highly paid.

4.2.2 Worker transitions between firms

Previous papers in the knowledge spillover literature have typically only been able to observe a worker's employment at a particular date each year. In the IDI worker data is observed at the monthly frequency and therefore can provide more detail regarding the exact timing of each move and also captures the entire population of moves. In terms of the model detailed in Section 3, there are two issues that need to be addressed in mapping the model to 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? Both of these issues are addressed below.

Regarding the source of the worker's knowledge when working multiple jobs, the approach taken in this paper is to assume that the productive knowledge a new worker brings to the

[19] Alternative measures of worker quality were also considered. Appendix A.6 presents results for the baseline estimated model where worker quality is measured as: (1) worker fixed effect only, and (2) workers wage less the firm fixed effect. This second measure is more likely to capture some of the worker-firm match quality. Overall, the alternative worker quality measures do not have a significant effect on the results.

hiring firm comes from a single source, which will be referred to as the worker's previous "main job". Informally, a worker's main job can be considered to be the one that they are in the best position to absorb the collective knowledge at one particular firm through a combination of spending more time at the firm than at others and/or working in a more prominent position within the firm. Both of these factors are expected to give them more opportunities to acquire new knowledge.

More formally, the "main job" prior to starting at a new firm 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.[20]

Two assumptions are made here. The first assumption is that the worker's knowledge is unlikely to depreciate over a short time period (three months, or one quarter), so all jobs in this window should be candidates for the worker's main job. The second assumption is that if a worker is paid more in one job that another, they are likely to be either working more hours and/or have a more important role within that particular job. Both of these factors are expected to facilitate their ability to absorb productivity knowledge from their previous employer. Therefore, the potential stock of knowledge the worker has should be more closely related to their higher-paying job.

In the cases where the new worker did not 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. Their previous main job is then the highest paid job for that particular month. The analysis of this paper does not make any allowance for depreciation of the worker's stock of knowledge and skills during jobless spells. As shown in the table 4 of the summary statistics, the average worker has a five month break between finishing their previous main job and starting their new one (with a median of zero months).[21]

To address the issue arising from the fact that firm productivity is only observed at an annual frequency while we observe worker movements at the monthly frequency, the following approach is taken. If a worker leaves their previous employer in the first six months of that employer's financial year, it is assumed 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

[20]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. This is predominantly an issue for the final month of employment at a job where the worker is likely to be paid out any outstanding annual leave accrued while working. This will bias upwards their income for that month, and not accurately reflect the effort put into working at the job for that particular month.

[21]Recall that with the way we are defining the "main job" it is possible for the worker to work at another firm for a month in between ending at the previous main job and starting at a new job.

year. Similarly, when the worker starts at their new firm, the hiring firm's productivity level is based on annual productivity for the year six months prior to the worker's start month. Hence if a worker arrives in the first six months of the firm's financial year, the hiring firm's knowledge used to compute the productivity gap is that of the previous financial year. If a worker arrives in the final six months of the firm's financial year, the hiring firm's knowledge used to compute the productivity gap is that of the current financial year.

4.3 Summary statistics

Table 2 describes the characteristics of the private-for-profit firms in the sample based on firm-year data. 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). If we interpret the aggregate productivity gap through the lens of exposure to new knowledge from other firms, the productivity gap suggests that due to labour mobility, the average worker in a hiring firm gains exposure to productive knowledge that is around half a percent higher than their employer's current level. 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.

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 labor (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 labor 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 full time employees, while the median firm employees the equivalent of around 18 full time employees on average across the year. The average firm also features a large amount of labor churn. On average, new workers, who were not employed by the firm during the previous financial year, supply just under 20 percent of the FTE labor units used by a firm in the current year. And workers who will leave the firm sometime during the year supply on average around 17 percent of the firm's labor input for that year. The large contributions by new and exiting workers contribute to an excess turnover rate of around 50 percent.[22]

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. These new workers are sourced from a wide variety of sources. Around 11 percent come from non-market firms, around 29 percent come from small firms (less than 5 FTE workers). More importantly, around 49 percent of observed hires 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. Most firms within the sample hire new workers each year. 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 labor force size, and have higher rates of labor market churn.

Table 3: Worker transitions — Value-added per worker

	Source of new employee hires													
Hiring firm's	**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.

[22] 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 labor in the final month of the firm's financial year.

Firms do not hire new workers randomly. There is often a lot of selection (on behalf of both the employer and employee) that goes into making a new employment match. Table 2 showed that hiring firms tend to have a lot of labor churn and hire many new workers each year. But where do these new workers come from? 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. As discussed in appendix C.3, the distribution of firm size in New Zealand conforms to Zipf's law, indicating a large fraction of small firms exists in the economy. Thus it is not too surprising to find this source supplies a large fraction of new hires to firms in each of the productivity deciles.

In terms of hiring from other PFP firms for which we are able to estimate the productivity level, firms do slightly favor sourcing new workers from similar productivity deciles. However, the size of this bias is very small, and even firms in the lowest productivity decile still obtain about 4 percent of their new workers from firms in the top productivity decile. The fact that all hiring deciles have similar hiring ratios from the various decile of PFP firms indicates that if the knowledge spillover story holds, a wide range of firms have access to the knowledge at the productivity frontier, although the gains the firm receives from this knowledge, and their ability to absorb the new frontier knowledge may be different.[23] Alternatively, if the unmeasured worker quality channel holds, then the least productive firms are able to hire the best quality workers.

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 (86.2 vs 84.5 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.

[23]These results differ from those for Danish manufacturing firms found by Stoyanov and Zubanov (2012) who identify a strong pattern of firms biasing their hiring towards workers from firms with similar productivity levels.

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. incument	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. Summary statistics reported as percentiles are the percentile within the firm (e.g. 0.45 implies the new worker is above 45 percent of workers in the firm). Summary 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). The human capital measure consists of the worker's fixed effect and contribution from observable characteristics (see section 4.2 for more details). FTE denoted Full Time Equivalent measure of labor. Real earnings are computed controlling for FTEs supplied.

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 below average pay (around 86 percent of the average pay), supply less FTE units of labor (88 percent of the average), and also be younger and less skilled than the average worker.[24] 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.

The final panel, Panel C, shows the worker's characteristics at their new job, relative to their own characteristics at their last main job. Taking a new job is profitable on average for workers. Their FTE-adjusted monthly earnings are around 13 percent higher than in their previous job, and they work supply around twice the FTE units of labor. This large increase in labor supply is primarily driven by part-time workers and those with multiple jobs transitioning to full-time jobs.[25] 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 of zero months break. As stated previously, we do not explicitly model depreciation of productive knowledge in the model. The results from these summary statistics tend to suggest that for most workers in the data set, the depreciation of skill/knowledge between jobs is not a significant concern. Around 20 percent of the worker moves observed in the data set are within the same 3-digit industry as their previous employer.

Overall, workers who move between firms tend to come from the lower half of the sending firm's pool of labor (in terms of earnings, age, and labor supplied), and they also tend to have a similar ranking in the firms that thy join. Caution should be applied when interpreting these worker-level summary statistics from the point of view of the productivity spillover story. The aggregate labor flows in the economy are dominated by workers who have a high turnover rate in their careers, and those that tend to work multiple jobs. These types of employees are less likely to be the main vector of productivity knowledge spillover between firms. For the majority of the analysis below, the spillover effects from new hires are examined based on a subset of new workers defined by various characteristics of the new hires and their previous employer. This approach attempts to control for the fact that not all new workers will be equal in terms of either the knowledge they have or their ability to transfer productive knowledge between firms.

[24]Because FTE is a derived measure of labor supply, there may be some measurement error in the amount of labor supplied by individual workers.

[25]The large variance seen the value of FTE supplied is drive by a relatively small number of outlier workers who work multiple jobs at the time of their previous employment (giving them a low FTE in their previous main job) and move to full time work at their new job. Some of these large changes could be due to the way FTEs are calculated. If a part-time worker moves to another part-time job it is possible for them to appear to become a full-time worker (or increase their labor supply) if their hourly pay increases by a sufficient amount.

5 Analysis

The regression analysis begins by considering the estimation of the baseline model for the various measures of firm productivity. This is conducted in section 5.1. The baseline model is then extended in section 5.2 to decompose the inflow of new workers into more granular categories as well as to estimate the model on subsets of the data. Doing so allows further testing of the predictions made by the various theoretical channels through which new workers can benefit the hiring firm.

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 labor force (column 1) and building up to the baseline model with separate productivity gaps for hires from more and less productive firms, defined by equations 5 and 4, in the final column. All results in the table are computed using value-added per worker (labor productivity) as the measure of firm productivity. When included, the lagged change in productivity $\Delta \ln A_{i,j,t-1}$ is instrumented using $\ln A_{i,j,t-2}$ to address the presence of the Nickell bias previously mentioned.

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 labor productivity of around 0.5 percentage points.

In reality, the firm can choose to change the quality of its average worker in three main ways. It can (i) hire new workers of different quality; (ii) let go some of its current workers; or (iii) change the number of hours worked by incumbent workers of different qualities.[26] Changing the average quality of the labor force via these different methods could have different costs to the firm in terms of productivity. For example, newly hired workers may take time to adjust and fit to the culture of the firm, limiting their influence on the firm's productivity. 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.[27]This

[26]In line with the way worker quality is measured in the data, we are ignoring here the possibility that firms selectively choose to invest in training of workers to raise the quality of the workers as this cannot be observed with the data set available.

[27]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 labor 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**	**more/less decomp.**	**Add productivity gap** **Aggregate prod gap**	**more/less decomp.**	**Add prod lags** **Aggregate prod gap**	**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 in the regressions is the change in log value-added ($\Delta \ln A_{i,j,t}$). 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

decomposition allows us to determine whether changing the average quality of the work force through new workers has a different effect on productivity growth when compared to changing the average quality of the work force through changing work hours by incumbent workers, potentially highlighting productivity costs to the firm associated with hiring new workers.

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 labor 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 labor via changes to the mixture of hours worked by incumbent employees.

The specifications in the third and fourth columns of table 5 add to the model the hiring intensities from various sources (number of new hires for each source, normalized by the size of the hiring firm), 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 labor 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 labor 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. Excess hires on the order of 10 percent of the firm's FTE labor supply is associated with a 0.4 percentage 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 comes 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. Now, the productivity gaps measure the intensive margin of hiring from PFP firms (the marginal benefit of sourcing from more productive firms), while the hiring intensity from the PFP firms measures the extensive margin of hiring (the effect due to the number of workers hired). When we consider 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.[28] Column six shows that if we disaggregate the productivity gap into separate productivity gaps for hires 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. Both the firm's productivity in period t and the firms hiring choices in period $t-1$ may be driven by past productivity developments within the firm. Therefore, it is important that we control for past productivity. 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 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, and around one third would be due to improvements in the unmeasured worker quality.

Labor 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.[29] The coefficients related to the productivity gaps for all productivity measures are positive and significant in magnitude. However, in the case of the Cobb-Douglas

[28] 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.

[29] Results based on a Cobb-Douglas model with firm-specific fixed effects are available in appendix B.2. In general, they do not vary significantly from the Cobb-Douglas results presented throughout the main body of the paper.

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 different (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 that are very similar, both economically, as well as statistically (p-value = 0.8).

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 both MFP measures, improving the average worker quality through new hires has a similar effect to improving the average worker quality through changing the mixture of incumbent workers. The Cobb-Douglas results imply improving the quality of average labor in the firm by one percent raises the firm's productivity by around 0.1 percentage points, while the trans-log results suggest the productivity gain will be around 0.16 percentage points.

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 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 relate to hires from more and less productive firms are not statistically different.

Only the baseline model estimated using value-added per worker as the measure of firm productivity provides support 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 labor productivity end up increasing their own capital utilization, this would appear as an increase in labor productivity, but not necessarily as an increase in MFP.[30] 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/total-factor productivity of the firm.

To investigate further the possibility that the knowledge spillover premium associated with the productivity gap from more productive firms over less productive firms relates to tech-

[30]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.

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 in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

nology knowledge and not efficiency, the baseline model is re-estimated using the firm's ratio of capital to labor as dependent variables 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.[31]

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 labor 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 improves productivity growth next period. 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 labor 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-labor 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.

[31] 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 labor productivity would capture. This issue is explored further in appendix A.1 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-labor 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-labor 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 eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2 Extensions to the model

In the remainder of 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 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.:

$$\begin{aligned}
\beta \Delta know_{i,t} \quad = \quad & \sum_{\text{ind}\in\{\text{same},\text{diff}\}} \beta_{M,ind} \frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_{\text{ind}}(n)\mathbb{D}_n[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \sum_{\text{ind}\in\{\text{same},\text{diff}\}} \beta_{L,\text{ind}} \frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_{\text{ind}}(n)(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}} \qquad (6)
\end{aligned}$$

where 'ind = same' denotes the hire is from the same industry, 'ind = diff' denotes the hire is from a different industry, $\mathbb{D}_{\text{ind}}(n)$ is a dummy variable based on the 'ind' classification. So when $\mathbb{D}_{\text{ind}}(n) = \mathbb{D}_{\text{same}}(n)$, $\mathbb{D}_{\text{same}}(n)$ takes on the value of 1 if worker n's previous main job was in the same industry (and a similar definition for the case when 'ind = diff'). Therefore, $\beta_{M,\text{same}}$ 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.[32] 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 of 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.[33]

The remaining parameters in the model are generally no significantly affected by the distinction between hires from within or between industries.Most notably, the coefficients related to the hire intensities (shown in table 8), which capture the effect of hiring intensity from the various sources, do not differ significantly with hiring from the same or different industries.[34]

[32] 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.

[33] An exception to this 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.

[34] The results in table 8 also provide a cross-check on potential bias created by using demeaned MFP measures to construct the productivity gap. Because MFP comparisons between firms in the same industry are not biased by differences between average industry productivity, comparisons of the productivity gap coefficients from hires from more and less productive firms within the same industry will not be biased. Because both the baseline results as well as the within the same industry results show productivity gap coefficients that are similar for hires from more and less productive firms, this lends further support to the idea that differences in between-industry average productivity are not biasing 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 in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 (since their knowledge is likely to be inferior), 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 from more and less productive firms 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

$$\begin{aligned}\beta \Delta know_{i,t} \quad = \quad & \sum_{\text{tenure}\in\{\text{long},\text{short}\}} \beta_{M,\text{tenure}} \frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_{\text{tenure}}(n)\mathbb{D}_n[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\ & + \sum_{\text{tenure}\in\{\text{long},\text{short}\}} \beta_{L,\text{tenure}} \frac{\sum_{n\in\mathcal{N}_i,t-1} \mathbb{D}_{\text{tenure}}(n)(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\ & + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}} \end{aligned} \tag{7}$$

where 'tenure = long' denotes workers with long tenure, 'tenure = 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 $\beta_{M,\text{tenure}}$ denotes the effect of the productivity gap associated with hires of workers from more productive firms who have long tenure at that firm.

One potential issue with the analysis of tenure described above is that it doesn't 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.

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.[35] 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

[35] 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 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 in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 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 the 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-labor 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-labor 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-labor ratio, we do find support for tenure benefiting the input-intensity gains, and this is consistent with the predictions of the knowledge spillover channel.

5.2.3 Worker's 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

Table 10: Effects of considering worker tenure — capital-labor 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-labor ratio ($\Delta \ln(K_{i,j,t}/L_{i,j,t})$). 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 eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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:

$$\begin{aligned}
\beta\Delta know_{i,t} \quad = \quad & \sum_{\text{skill}\in\{\text{low,med,high}\}} \beta_{M,\text{skill}} \frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_{\text{skill}}(n)\mathbb{D}_n[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \sum_{\text{skill}\in\{\text{low,med,high}\}} \beta_{L,\text{skill}} \frac{\sum_{n\in\mathcal{N}_i,t-1} \mathbb{D}_{\text{skill}}(n)(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}} \qquad (8)
\end{aligned}$$

where 'skill = low' denotes a worker skill in the bottom third of the distribution of worker quality, 'skill = med' denotes a worker skill in the middle third of the distribution of worker quality, and 'skill = high' denotes a worker skill in the top third of the distribution of worker quality. $\mathbb{D}_{\text{skill}}(n)$ is a dummy variable that takes on the value 1 if worker n is in the skill third of the distribution of worker quality. *less* and *more* again refer to the productivity of the worker's previous firm relative to the hiring firm's productivity.

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 labor 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.

The coefficients related to productivity gap for hires from less productive firms are similar in

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 in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 labor 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 labor is utilised differently in the production process when compared to medium and high skilled labor (e.g. only low skill workers perform manual labor jobs while higher skilled labor is used to perform other tasks). The measures of productivity so far assume that labor is a homogenous input into the production process. If low skilled labor is in effect utilised differently to medium and high skilled labor, the production function specifications used may not fully capture the distinction between low and other skilled labor 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 labor productivity. This is consistent with the unmeasured worker quality channel. Furthermore, because the value-added and MFP results do not differ dramatically, this also suggests that worker skill is not an important determinant of the productivity knowledge spillover seen in labor productivity results.

5.2.4 Earning rank at hiring firm

The effect of a worker's knowledge on the hiring firm is also likely to differ depending upon the job they perform within the hiring firm. For example Maliranta et al. (2008) finds that hiring workers from another firm's R&D lab to work in the hiring firm's R&D lab "does not seem to be a significant spillover channel." However, hiring from another firm's R&D lab into non-R&D roles boosts productivity and profitability of the hiring firm. One of the limitations of the IDI data set is that it does not provide detailed information as to the jobs of workers. Therefore, the worker's relative pay within the firm is the best proxy that is available for the job type of the worker.

To examine what relation, if any, exists between the jobs of new workers and the productivity growth at the hiring firm, the inflow of workers from more and less productive firms are divided into low paid workers, and high paid workers. This should allow us to distinguish between the types of jobs that workers perform, as the highest paid workers at a firm are more likely to be specialists and managers, and lower paid workers are more likely to work in more generalized jobs. The cutoff for high paid workers is based on the percentile ranking of the workers relative to the rest of the firm's workforce in the first month after hiring. Formally, the change in the hiring firm's stock of productive knowledge is modelled as:

$$
\begin{aligned}
\beta \Delta know_{i,t} \quad = \quad & \sum_{\text{pay}\in\{\text{low,high}\}} \beta_{M,\text{pay}} \frac{\sum_{n\in\mathcal{N}_{j},t-1} \mathbb{D}_{\text{pay}}(n)\mathbb{D}_{n}[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \sum_{\text{pay}\in\{\text{low,high}\}} \beta_{L,\text{pay}} \frac{\sum_{n\in\mathcal{N}_{i},t-1} \mathbb{D}_{\text{pay}}(n)(1-\mathbb{D}_{n})[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_{s} \frac{H_{i,s,t-1}}{L_{i,t-1}} \qquad (9)
\end{aligned}
$$

where 'pay = low' denotes workers paid in the lower percentile rankings of the firm and 'pay = high' denotes workers paid in the higher percentile rankings of the firm. $\mathbb{D}_{\text{pay}}(\text{n})$ is a dummy variable that takes on the value 1 if worker n is earning income that is 'pay' relative to the earnings cutoff value.

Table 12 presents the results of estimating the extended baseline model with distinctions for high and low paid workers. Two definitions of high paid workers are used. The first defines high paid workers are those who earn in the top 10 percent of workers at the firm one month after starting. The second set of results uses 20 percent as the cutoff value.

The coefficients related to the productivity gaps for high and low paid workers are very different from one another. While the productivity gap coefficients related to low paid workers are similar to the estimated coefficient values from baseline estimation, the productivity gap coefficients related to high paid are dramatically smaller, and in the case of the MFP measures even negative (although not significantly so). However, the coefficients related to hires of high paid workers are very imprecisely measured. The summary stats from table 4 show that the average new hire from more productive firms earn below the average wage in the hiring firm. Therefore, we are likely lacking the power to properly test the coefficient values.

It is difficult to align the results from table 12 with the standard predictions made by the theoretical channels considered in this paper. While it is possible that highly paid workers are associated with less change in the hiring firm's productivity (both in terms of labor productivity and MFP), there are ex-post justifications as to why we might expect mixed results. For example, selection effects related to the types of workers that move into high and low paid jobs at firms as well as the types of firms that hire into high and low paid jobs

Table 12: Worker flows by worker earnings at hiring firm

	Value-added			**Cobb-Douglas**			**Trans-log**		
	Baseline	**High earning cutoff value**		**Baseline**	**High earning cutoff value**		**Baseline**	**High earning cutoff value**	
		10%	**20%**		**10%**	**20%**		**10%**	**20%**
Prod. gap, hires from (β):									
More prod. firms	0.480***			0.271***			0.354***		
	(0.098)			(0.065)			(0.068)		
High paid workers		0.114	0.360		-0.062	-0.254		-0.246	-0.155
		(0.373)	(0.254)		(0.317)	(0.220)		(0.389)	(0.277)
Low paid workers		0.516***	0.503***		0.290***	0.340***		0.399***	0.439***
		(0.102)	(0.118)		(0.067)	(0.079)		(0.077)	(0.095)
Less prod. firms	0.153***			0.374***			0.374***		
	(0.030)			(0.054)			(0.056)		
High paid workers		0.049	-0.012		0.178	0.423		-0.450	0.050
		(0.149)	(0.124)		(0.385)	(0.295)		(0.274)	(0.208)
Low paid workers		0.158***	0.175***		0.390***	0.366***		0.431***	0.429***
		(0.033)	(0.032)		(0.064)	(0.080)		(0.059)	(0.069)
Hire intensity (λ):									
More prod. firms	-0.200***			-0.012			-0.037*		
	(0.057)			(0.028)			(0.021)		
High paid workers		-0.168	-0.242		0.080	0.096		0.072	0.076
		(0.216)	(0.149)		(0.114)	(0.081)		(0.104)	(0.074)
Low paid workers		-0.202***	-0.191***		-0.017	-0.024		-0.046**	-0.058**
		(0.058)	(0.063)		(0.029)	(0.032)		(0.023)	(0.027)
Less prod. firms	-0.117***			0.047*			0.004		
	(0.027)			(0.026)			(0.019)		
High paid workers		-0.142	-0.101		0.158	0.156		-0.043	0.040
		(0.121)	(0.086)		(0.131)	(0.096)		(0.080)	(0.061)
Low paid workers		-0.114***	-0.116***		0.039	0.029		0.007	-0.000
		(0.028)	(0.029)		(0.028)	(0.032)		(0.019)	(0.021)
Parameter tests:									
$\Pr(\beta_{M,high} = \beta_{L,high})$		0.872	0.182		0.643	0.079		0.657	0.557
$\Pr(\beta_{M,low} = \beta_{L,low})$		0.001	0.006		0.273	0.807		0.742	0.934
$\Pr(\beta_{M,high} = \beta_{M,low})$		0.300	0.636		0.286	0.025		0.128	0.081
$\Pr(\beta_{L,high} = \beta_{L,low})$		0.492	0.159		0.610	0.870		0.003	0.121
Obs.	37269	37269	37269	28260	28260	28260	28260	38037	38037

Notes: The dependent variable in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), where the measure of productivity differs by column. Low and high skill is determined by the cutoff value using the new worker's earnings ranking in the first full month of employment relative to all other workers at the 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

could be influencing the magnitudes of the effects seen in the regression results. Becoming a high paid worker in a particular firm does not necessarily mean that the worker is highly paid relative to the rest of the economy. Likewise, highly paid and skilled workers may be moving into firms who tend to employ highly skilled workers. Hence these new highly paid and skilled workers could be in the lower part of the pay distribution within the firm. Without more detailed control variables to distinguish between different types of high paid workers, these results should be interpreted with some caution.

5.3 Robustness

The regression analysis conducted so far only implies correlation between the hiring of new workers and productivity growth in the hiring firm. It does not imply causality which would be needed to definitively which of the various channels considered was the true drivers of productivity growth in the hiring firms. The analysis in this section attempts to control for causality within the model, and deal with other issues of robustness of the results.[36]

5.3.1 Reverse causality

All of the channels considered so far in this analysis for how new workers benefit the hiring firms have implied that causality runs in the direction of new hires affecting productivity. Even though the survey data from the BOS tells us that at least some causality runs in the directions of new hires to innovation, one cannot rule out that at least some causality runs in the opposite direction, i.e. that changes (or expected changes) in firm productivity drive hiring. For example, it is also plausible that the hiring firms develop their own improvements to productivity, and to take advantage of these productivity improvements the firms hires new workers with specific skills and knowledge to complement their new production approach.

To properly control for this effect 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 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 labor and capital inputs, allowing us to estimate the component of MFP excluding the productivity shocks observed by the firm, thereby avoiding the reverse causality.[37]

[36] Additional robustness checks are presented in appendix A.

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

Table 13 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.[38] 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 coefficient on the productivity gaps for hires from more and less productive firms was not statistically significant in the Cobb-Douglas case, the two coefficients have 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 favor 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 limitations of the data available.[39]

5.3.2 Additional instruments for $\Delta \ln A_{i,j,t-1}$

Lagged productivity is an important control in the model. Today's productivity growth as well as the firm's hiring decisions are likely to be correlated with lagged productivity. However, as mentioned in section 3, including $\Delta \ln A_{i,j,t-1}$ in the regression is problematic due to the presence of large Nickell bias in the data. Therefore, in the baseline model $\ln A_{i,j,t-2}$ is used as an instrument for $\Delta \ln A_{i,j,t-1}$. However, $\ln A_{i,j,t-2}$ is not the only instrument that can be used for $\Delta \ln A_{i,j,t-1}$. Blundell and Bond (1998) developed a technique that extends the Arellano-Bond estimation to include both the lagged levels and lagged differences of productivity as suitable instrumental variables in the estimation of dynamic panel models.

Table 14 reports the results of estimating the model using the Blundell and Bond (1998) approach with extra instruments for the change in lagged productivity ($\Delta \ln A_{i,j,t-1}$) against the baseline regressions. For all three productivity measured considered, the coefficients in the model do not change dramatically with the inclusion of additional instruments for past

[38]The Stata function 'levpet' developed by Petrin et al. (2004) is used to construct the Levinsohn-Petrin productivity measure.

[39]Some attempts were made to estimate the model on the subset of firms in the data set that were also BOS survey respondents. Doing so would allow for the model to be estimated on firms that have told us the causality runs in the direction of new hires to innovations in the hiring firm. While the estimates from this work were broadly in line with the magnitudes reported throughout this paper, implying reverse causality is not a significant issue, because of the relatively small number of BOS respondents in our data set, as well as differences in the timing of the BOS survey and the financial data, it is difficult to be confident that we can provide a good mapping from our model to the BOS data. As a result we have chosen not to present the results based on the BOS respondents in this paper.

Table 13: 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 in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

productivity. From these results, we can conclude that the results of our analysis are not sensitive to the inclusion of additional instruments.

Table 14: Effect of additional instruments for lagged productivity

	Value-added		Cobb-Douglas		Trans-log	
	Baseline	**Blundell-Bond**	**Baseline**	**Blundell-Bond**	**Baseline**	**Blundell-Bond**
Productivity gap, hires from (β):						
More prod. firms	0.480***	0.515***	0.271***	0.257**	0.354***	0.250***
	(0.098)	(0.124)	(0.065)	(0.112)	(0.068)	(0.093)
Less prod. firms	0.153***	0.172***	0.374***	0.363***	0.374***	0.296***
	(0.030)	(0.043)	(0.054)	(0.086)	(0.056)	(0.075)
Hire intensity (λ):						
More prod. firms	-0.200***	-0.193***	-0.012	-0.018	-0.037*	-0.027
	(0.057)	(0.063)	(0.028)	(0.030)	(0.021)	(0.021)
Less prod. firms	-0.117***	-0.108***	0.047*	0.044	0.004	0.007
	(0.027)	(0.027)	(0.026)	(0.027)	(0.019)	(0.018)
Obs.	37269	49920	28260	38049	38037	50874

Notes: The dependent variable in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), where the measure of productivity differs by column. The Blundell-Bond columns report regression results using lags of productivity ($\ln(A_{i,t-x})$) and change in productivity $\ln(A_{i,t-x})$ as instruments for past productivity. 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.3.3 Scale of the productivity gap

The productivity gap terms in equation 3 is constructed following the approach of Stoyanov and Zubanov (2012) and normalizes the sum of the productivity differentials by the size of the hiring firm's labor force.[40] This functional form implicitly assumes that to achieve the same percentage point increase in the hiring firm's productivity growth, a large firm need to absorb a larger amount of productive knowledge from new hires than a small firm would. While this is a reasonable assumption for knowledge that relates to specific roles/jobs within a firm, it is not necessarily true for all types of knowledge. Some knowledge may be equally applicable to firms, regardless of their size, such as firm restructuring.

To investigate this concern, the baseline model is modified to include terms for the average productivity difference between the sending and hiring firm so the change in the firm's productive knowledge stock now takes the form

$$\begin{aligned}
\beta\Delta know_{i,t} \quad = \quad & \beta_M \frac{\sum_{n\in\mathcal{N}_j,t-1}\mathbb{D}_n[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& +\beta_{M,2}\frac{\sum_{n\in\mathcal{N}_j,t-1}\mathbb{D}_n[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{H_{i,M,t-1}} \\
& +\beta_L\frac{\sum_{n\in\mathcal{N}_i,t-1}(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& +\beta_{L,2}\frac{\sum_{n\in\mathcal{N}_i,t-1}(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{H_{i,L,t-1}} \\
& +\sum_{s\in\mathcal{S}_{i,t-1}}\lambda_s\frac{H_{i,s,t-1}}{L_{i,t-1}} \qquad (10)
\end{aligned}$$

where $H_{i,M,t-1}=\sum_{n\in\mathcal{N}_j,t-1}\mathbb{D}_n$ is the number of new hires from more productive firms, and $H_{i,L,t-1}=\sum_{n\in\mathcal{N}_j,t-1}(1-\mathbb{D}_n)$ is the number of new hires from less productive firms. In this new specification, β_M and β_L will relate to the benefit of new knowledge that scales with the size of the hiring firm, while $\beta_{M,2}$ and $\beta_{L,2}$ will related to the benefit of knowledge that is independent of the firm size.

Another potential issue with the scaling of the productivity gaps is there may be some economies, or dis-economies, of scale with regards to absorbing new knowledge. If there are limits on how quickly firms can adapt and implement new knowledge, then the marginal benefit of obtaining large amounts of new knowledge within a single year will be small. In such cases, the relationship between the productivity gap and productivity growth may not be linear.

Non-linearities in the ability to absorb new knowledge are also likely when a firm has a high staff turnover rate. A firm with a high turnover rate will tend to have a high productivity gap simply because of the number of hires they make each year. But despite the high number

[40] An alternative interpretation is that the productivity gap is the average productivity differential multiplied by the intensity of new hires.

of hires, staff may not remain with the firm long enough for the firm to fully benefit from the new knowledge. To investigate if this is the case, the baseline model is augmented with the squared productivity gap to capture any non-linearities in the relationship between the productivity gap and the productivity growth in the hiring firm. Therefore the change in the hiring firm's productive knowledge would take the form

$$\begin{aligned}
\beta\Delta know_{i,t} \;=\; & \beta_M \frac{\sum_{n\in\mathcal{N}_j,t-1}\mathbb{D}_n[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& +\beta_{M,3}\left(\frac{\sum_{n\in\mathcal{N}_j,t-1}\mathbb{D}_n[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{L_{i,t-1}}\right)^2 \\
& +\beta_L \frac{\sum_{n\in\mathcal{N}_i,t-1}(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& +\beta_{L,3}\left(\frac{\sum_{n\in\mathcal{N}_i,t-1}(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta})-\ln(A_{i,t-1-\delta})]}{L_{i,t-1}}\right)^2 \\
& +\sum_{s\in\mathcal{S}_{i,t-1}}\lambda_s\frac{H_{i,s,t-1}}{L_{i,t-1}} \qquad (11)
\end{aligned}$$

Table 15 presents the regression results found when augmenting the baseline model to include (i) the non-normalized productivity gap, and (ii) the squared productivity gap.

Table 15: Additional productivity gap dynamics

	Value-added			**Cobb-Douglas**			**Trans-log**		
	Baseline	**+ non-norm gap**	**+ sqrd prod gap**	**Baseline**	**+ non-norm gap**	**+ sqrd prod gap**	**Baseline**	**+ non-norm gap**	**+ sqrd prod gap**
Productivity gap, hires from (β):									
More prod. firms	0.480***	0.388***	0.959***	0.271***	0.219**	0.401***	0.354***	0.082	0.616***
	(0.098)	(0.097)	(0.087)	(0.065)	(0.087)	(0.068)	(0.068)	(0.073)	(0.084)
Less prod. firms	0.153***	0.243***	0.176***	0.374***	0.400***	0.519***	0.374***	0.310***	0.519***
	(0.030)	(0.063)	(0.042)	(0.054)	(0.077)	(0.076)	(0.056)	(0.073)	(0.063)
Non-normalized prod. gap									
More prod. firms		0.067***			-0.005			0.076***	
		(0.014)			(0.013)			(0.016)	
Less prod. firms		-0.021**			0.023			0.005	
		(0.010)			(0.015)			(0.011)	
Squared productivity gap									
More prod. firms			-0.188***			-0.150**			-0.192***
			(0.024)			(0.073)			(0.041)
Less prod. firms			0.005			0.107***			0.147***
			(0.004)			(0.038)			(0.052)
Hire intensity (λ):									
More prod. firms	-0.200***	-0.171***	-0.392***	-0.012	-0.006	-0.046*	-0.037*	0.033	-0.097***
	(0.057)	(0.058)	(0.050)	(0.028)	(0.035)	(0.026)	(0.021)	(0.021)	(0.024)
Less prod. firms	-0.117***	-0.012	-0.075**	0.047*	0.062**	0.086***	0.004	-0.005	0.042**
	(0.027)	(0.036)	(0.030)	(0.026)	(0.031)	(0.028)	(0.019)	(0.022)	(0.018)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.001	0.208	0.000	0.217	0.113	0.228	0.808	0.025	0.327
$\Pr(\lambda_M = \lambda_L)$	0.237	0.028	0.000	0.145	0.159	0.001	0.174	0.240	0.000
Obs.	37269	23199	37269	28260	18423	28260	38037	23877	38037

Notes: The dependent variable in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

When using labor productivity (value-added per worker) to measure firm productivity, the inclusion of the non-normalized productivity gap (equation 10) does not seem to have a significant effect on estimated magnitudes of the original productivity gap terms. The coefficient on the productivity gap related to hires from more productive firms declines only slightly (from 0.48 to 0.388), while the coefficient on the productivity gap related to hires from less productive firms increases slightly from 0.153 to 0.242.

The coefficients related to the non-normalized productivity gaps (measuring the benefit of new knowledge not affected by the size of the hiring firm) are both estimated to be significant, but smaller in magnitude than the corresponding productivity gap coefficients. Surprisingly, the coefficient on the non-normalized productivity gap from less productive firms is negative. Because the productivity difference with less productive firms is negative, the negative coefficient implies that sourcing the average worker from even less productive firms raises productivity growth in the hiring firm. While this result in isolation is unexpected, it should also be noted that the coefficient on the standard (normalized) productivity gap for hires from less productive firms grew in magnitude. This will offset the supposed productivity gains through the non-normalized productivity gap when hiring from less productive firms.

For the Cobb-Douglas measure of firm productivity, the coefficients on the non-normalized productivity gaps are generally smaller. In addition, the other parameters in the model are generally unaffected by the inclusion of the non-normalized productivity gaps. However, for the trans-log measure of productivity, the results show that the productivity gains associated with hiring from more productive firms are more closely associated with the average productivity difference from new hires (the non-normalized productivity gap) rather than the (normalized) productivity gap adjusted for firm size. The estimated coefficient on the productivity gap related to hires from more productive firms declines significantly (from 0.354 to 0.082), and the coefficient for the non-normalized productivity gap (0.076) is significant. This suggests that when using trans-log productivity, the gains associated with the exposure to new and better productive knowledge tends to be independent of the hiring firm's size. Because the trans-log productivity measure is more flexible to changes in the firm's production structure than the Cobb-Douglas measure, this suggests that firms adapt their production technology in response to new and better knowledge.

When the squared productivity gap term is added to the baseline model we see two main patterns emerge in the parameter values across all the productivity measures. First, the magnitude of the coefficients on the original productivity gaps increase. Second, the coefficient on the squared productivity gaps are negative for hires from more productive firms, and positive for hires from less productive firms.

The negative coefficient on the squared productivity gap for hires from more productive firms is similar in magnitude to across all productivity measures, and implies a concave function for the correlation with productivity growth at the hiring firm. Therefore the marginal gain from a larger productivity gap is decreasing, and for very large values of the productivity gap, the expected gains in productivity growth can even be negative.

With regards to hires from less productive firms, the coefficients related to the squared productivity gaps are positive, and significant in the cases of the MFP measures. This implies that the marginal productivity loss associated with hiring from less productive firms is increase with the size of the productivity gap.

Overall, these results show some support for non-linearities in relation to the benefit of new knowledge for the hiring firm. However, even when accounting for these non-linearities, the coefficients related to the original productivity gaps are not dramatically affected.

5.3.4 More worker quality controls

Stockinger and Wolf (2016) found that for German firms, hiring from more productive firms was not correlated with productivity gains at the hiring firm, but hiring from less productive firms was. Their analysis reveals that there is a strong selection effect occurring, where the workers who move from more to less productive firms tend to be the workers who are among the lowest paid in their firm, and the workers who move from less to more productive firms tend to be the from the highest paid in the firm. To explore whether such a selection effect is influencing the estimates of the productivity gap and hire intensity coefficients in this paper's analysis, the approach of Stockinger and Wolf (2016) is adapted to the baseline model.

Since we are unable to observe the reason for the hiring firm's recruitment choices, it is possible that the types of workers the firms recruit are correlated with the productivity level of the worker's previous firm (e.g. hire only managers from productive firms, and production line workers from less productive firms). As a result, the coefficient on the productivity gap variables will be biased as it is measuring two factors, the productivity knowledge from new workers, and the job-type of these new workers.

As an attempt to control for this, two different measures of the worker's rank within the sending firm are used. The average ranking of new workers' pay, and the average ranking of new workers' previous human capital. Recall that the human capital measure is constructed from a log-wage regression so both rankings used as controls are correlated with one another, so one should expect that the results should not be too dis-similar. Table 16 presents the results of estimating the baseline model with these additional controls.

Table 16: Additional controls for the types on new workers hired

	Value-added			**Cobb-Douglas**			**Trans-log**		
	Baseline	**Additional controls:**		**Baseline**	**Additional controls:**		**Baseline**	**Additional controls:**	
		real earn. ranking	**quality ranking**		**real earn. ranking**	**quality ranking**		**real earn. ranking**	**quality ranking**
Productivity gap, hires from (β):									
More prod. firms	0.480***	0.478***	0.530***	0.271***	0.269***	0.199***	0.354***	0.352***	0.266***
	(0.098)	(0.098)	(0.082)	(0.065)	(0.064)	(0.060)	(0.068)	(0.068)	(0.078)
Less prod. firms	0.153***	0.144***	0.131**	0.374***	0.374***	0.448***	0.374***	0.370***	0.324***
	(0.030)	(0.030)	(0.041)	(0.054)	(0.054)	(0.066)	(0.056)	(0.055)	(0.056)
Earnings pctile rank within:									
More prod. firms		0.043***			0.005			0.010**	
		(0.007)			(0.006)			(0.004)	
Less prod. firms		-0.034***			-0.015*			-0.010**	
		(0.009)			(0.007)			(0.005)	
Worker qual. pctile rank within:									
More prod. firms			-0.125***			0.003			0.001
			(0.019)			(0.013)			(0.009)
Less prod. firms			-0.015			-0.040***			-0.008
			(0.020)			(0.015)			(0.012)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.001	0.001	0.000	0.217	0.206	0.004	0.808	0.834	0.533
$\Pr(\lambda_M = \lambda_L)$	0.237	0.131	0.001	0.145	0.107	0.047	0.174	0.116	0.537
Obs.	37269	37269	23199	28260	28260	18423	38037	38037	23877

Notes: The dependent variable in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$).The average rank at the previous firm is measured as the average percentile ranking of the worker's who leave to be hired by the hiring 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 results show that the key coefficients in the regression are unaffected by the inclusion of the additional controls. Therefore, it does not appear that the knowledge gap variables is proxying for the (measurable) quality of workers within their previous firm. So unlike the German data, there does not seem to be a significant selection effect in the types of workers hired from more and less productive firms within the New Zealand data.

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. Improving the average productivity level of the private-for-profit firms these workers are sourced from increased productivity growth at the hiring firm (on average). This relationship holds whether labor productivity (value-added per worker) or multi-factor productivity is used as the measure of firm productivity.

The findings also show that the labor productivity gains at the hiring firm associated with improving the average productivity of the firms that new workers are sourced from is on average larger (smaller) if the increase in the average productivity is driven by improvements in the productivity of sources 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 spend 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-labor ratio) is used instead of productivity.

In terms of multi-factor productivity, the gain associated with improving the average productivity of firms that new workers are sourced from does not depend on 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. In addition, these gains are not dramatically affected by the characteristics mentioned above. This suggests that the labor productivity premium associated with hiring from more productive firms relates to changes in technology (the capital intensity of the production function), rather than multi-factor productivity.

While these regressions 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. Even after controlling for the (measured) quality of the average worker in the firm, the productivity of the previous employers of new workers show correlation with the productivity growth in the hiring firm.

These findings are consistent with a worker quality/screening channel where more productive firms are either better at screening good quality workers, or provide them with better training. 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. This is what occurs in the MFP results. Finally, 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 value-added productivity measure, and the capital-labor ratio, but not the MFP data, would suggest the knowledge spillover related to knowledge about production technology (more capital intensive production methods), not MFP (how to utilize the firm's current inputs more efficiently).

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