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Worker flows, entry, and productivity in New Zealand's construction industry

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Abstract

We use administrative data on the population of New Zealand construction firms from 2001-2012, along with linked data on their employees and working proprietors, to study the relationships among worker flows, entry, and firm productivity. We find that job churn is prevalent in construction, with around 60 percent of firm-worker pairs not existing previously or not existing subsequently. Firms with new employees are more productive than those with no change in workforce, in part because of knowledge flows from other construction firms. In our preferred specification, with firm fixed effects, a standard deviation increase in the productivity of new employees' previous firms is associated with a 0.6 percent increase in productivity. Entrants are more productive than pre-existing firms. Firms that enter briefly and disappear exhibit high productivity for that brief period, and firms that enter and stay exhibit a persistent productivity advantage that averages about 6 percent, but which grows as experience accumulates. The entry and worker-knowledge-flow phenomena are distinct, in that the entry effect is not explained by employee composition, and non-entrant firms also benefit from worker knowledge flows.

JEL codes

D24, L74, J63

Keywords

Firm productivity, firm churn, job churn, creative destruction, knowledge flows

Summary haiku

Workers come and go.

Good for productivity.

Entry also helps.

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1 Introduction

From Josef Schumpeter in 1942 (Schumpeter, reissued 2013) to the most recent OECD report on the NZ economy (OECD 2017), economists have emphasized the dynamic reallocation of workers and other resources, including the birth and death of firms, as key determinants of aggregate productivity growth. Despite widespread concern that firm churn is a drag on productivity in New Zealand's construction industry, Jaffe et al. (2016) show that churn contributes positively to productivity growth. This occurs because new firms tend to be more productive than exiting firms, so that replacing such exiting firms with productive entrants boosts the industry's overall productivity. Jaffe et al. (2016) also find that new firms tend to be more productive than continuing firms.

The finding that new firms are more productive than exiting firms is common in the international literature (Baily et al. 1992, Aw et al. 2002, Foster et al. 2008, and Stanfield et al. 2008) and is healthy manifestation of Schumpeter's 'creative destruction'; underperforming firms are unprofitable and so leave in a process of natural selection. The more surprising finding is that new firms are more productive than continuing firms. This is puzzling because we tend to think that people learn over time, and so the productivity of firms ought to increase with experience (Jovanovic 1982, Bahk and Gort 1993, Jensen et al. 2001, Hyytinen and Maliranta 2013).

One characteristic of new firms is that their employees have to have come from somewhere else. We expect that a firm's productivity is, in part, a result of its employees' human capital, so it is natural to wonder if the productivity of entrants is related to their employees. Further, if the higher productivity of entrants is indeed related to the employees that they attract, it is then natural to ask if ongoing firms could get the same productivity advantage if they could attract the same kind of employees. In this paper we explore empirically the interaction of the entry and exit of firms with the movement of employees across firms, both to entrants and between existing firms. We investigate this using linked employer-employee data on all construction-industry jobs in New Zealand from 2001 to 2012. We hypothesize that the flows of workers across construction firms is a source of knowledge transfer, and that these knowledge flows are part of the reason new construction firms perform well. More generally, we also use these comprehensive data to document the flows of workers (employees and working proprietors) between firms and address the following questions:

1. How often do people change employers in construction, and how important is new labour to firms in construction?
2. Does the amount and source of new labour matter to firm productivity? Are firms more productive when their new workers come from a certain source, such as other construction firms?

3. To what extent do people bring productivity with them when they change firms, i.e., do people moving from high productivity firms tend to raise the productivity of their new employer through knowledge flows? Is the extent of this productivity transfer the same for new hires at new-entrant firms and new hires at continuing firms?
4. Why is the time pattern of productivity at entrant firms? Are new firms most productive when they first enter, or does their productivity improve as they gain experience?

The construction industry is particularly suitable for this analysis, because of the apparent tension between 'conventional wisdom' about the role of firm churn and the recent findings of productive entrants, and also because the small size of most firms likely increases the importance of individual workers with respect to firm performance.

To preview our findings, we show that:

- Entrant firms are observationally different from firms that were active in construction at the start of this period. They are more productive on average, they grow faster, and their productivity continues to improve over time. Accounting for observable differences in the composition of their work force reduces the 'entrant effect' somewhat but does not eliminate it.
- The finding in our own previous paper that the productivity advantage of entrants is largest in their first year appears to be an anomaly resulting from not having properly accounted for the unbalanced nature of our panel data, which means that the 'first year' effect in our data conflates the performance in the first year of firms that then stay around with the first year of firms that enter and then quickly exit. Once we control for such differences, we find that the productivity advantage of entrants is smaller in their first year, and the productivity performance of entrants then improves for at least a few years after entry.
- Workers frequently move in and out of jobs in construction, with an overall job churn rate of around 60 percent in most years. Firms (new or existing) that have new workers in a given year show higher productivity in that year. More generally, firm growth is associated with firm productivity improvement, though we cannot say anything about causality in this relationship.
- After controlling for these two effects, it is also true that firms whose employees previously worked at another high-productivity construction firm are themselves more productive. Thus we find meaningful evidence that firm-productivity is to some extent embodied in workers and workers can transfer high productivity across firms.

Thus overall we find that the dynamic movement of employees across firms and of firms in and out of the construction industry are important factors associated with productivity improvement at the micro level.

In a supplementary analysis, we find that less productive firms tend to have more new migrant labour, but that productivity doesn't decrease when a given firm hires more migrants.

While these estimates are not causal, they are better than nothing and suggest that whether new workers come from overseas or from other industries matters little to firm productivity. This may have relevance to the government's plan to build 100,000 new homes in the next decade, which will boost the size of the industry and the number of workers needed.

The rest of the paper is organised as follows: Section 2 provides background and discusses relevant New Zealand and international research; Section 3 outlines the data used; Section 4 presents descriptive statistics on job churn and new labour in construction firms; Section 5 details our empirical strategy and presents regression results; and Section 6 concludes and discusses the implications.

2 Background

Our study is related to two main strands of literature. The first strand documents the extent of firm churn and its correlation with aggregate productivity growth. The international evidence suggests that churn's contribution tends to be small but positive. This holds for manufacturing in the United States (Bailey et al., 1992; Bartelsman and Dhrymes, 1998), manufacturing and mining in Israel (Griliches and Regev, 1995), manufacturing in Chile (Liu, 1993), and manufacturing in Taiwan (Aw et al., 2001). Broad overviews are given by Bartelsman et al. (2004) and Kocsis et al. (2009), who document the importance of firm churn in reallocating resources in developed and developing countries, and its positive correlation with productivity growth. In New Zealand, Doan et al. (2012) document the prevalence of firm churn and find that it is procyclical, while Law and McLellan (2005) find that net firm entry is negatively associated with industry labour productivity. In contrast, Maré et al. (2016) look at a different time period and consider multi-factor productivity (MFP) growth. They find that although entrants and exiters tend to be less productive than continuers, the net contribution of firm churn tends to be positive.

This literature highlights two main channels through which churn affects industry productivity. The first is the direct channel of reallocating resources towards the most productive firms. Firms that are going to exit tend to suffer the 'shadow of death' of lower productivity (Griliches and Regev, 1995), and so their exit releases the firms' capital and labour to be used by more productive entrants and incumbents. If exiting firms tend to be less productive than entrants, then firm churn will directly increase productivity. If entrant firms are also more productive than continuers (as in Jaffe et al. 2015 for construction), then firm churn will boost productivity by an even larger amount.

The second channel through which churn may improve productivity is indirect. The threat of entry creates competitive pressure for incumbent firms. Increased competition may then spur innovation and, ultimately, productivity growth. Together, this churn underlies the creative destruction that Schumpeter believed was the 'essential fact about capitalism' (Schumpeter, reissued 2013).

A second strand of related literature looks at the flows of employees across firms, and the extent to which this correlates with firm performance. Thanks to the increased availability of linked employer-employee data, research into worker flows has been expanding. Yet, few studies have linked these flows to firm performance. Bjelland et al. (2011) document these flows in the US, showing that they make up around 4 percent of quarterly employment and 29 percent of main job separations; that they are procyclical; that employees with less education tend to switch employers more; and that over half of employee switches are between industries (using the broadest grouping of industries). Other studies also show that job flows are large, with a lot of dynamism in various economies (Hopenhayn and Rogerson 1993, Davis et al. 2006).

Maliranta et al. (2009) use Finnish data to examine whether workers spread R&D-generated knowledge when moving between firms. They conclude that knowledge from new employees can be readily implemented by firms, because hiring an employee previously in an R&D role boosts firm performance only when moving the employee into a non-R&D role. Campbell et al. (2012) examine employer-employee flows in US legal services, and find that wealthier employees are less likely to leave a firm but are more likely to create a spin-out firm conditional on leaving. They also find firm performance is hurt more when an employee leaves to form a spin-out firm than to become an employee at another firm.

Together, this literature documents that both firm and employee churn are widespread; that churn gives rise to creative destruction that boosts aggregate productivity; and that employee flows into and out of firms are correlated with firm performance.

Our study extends this literature by exploring worker flows and productivity in construction, an industry dominated by small firms for whom new workers are likely to be especially important. We also explore the extent to which the first set of findings (the positive contribution of firm churn) can be explained by the second set of findings (the importance of worker flows), by looking at entrant effects after controlling for the past productivity of new workers.

3 Data

This study uses rich administrative data from Statistics New Zealand's Integrated Data Infrastructure (IDI) and Longitudinal Business Database (LBD), which are collections of datasets containing longitudinal information on individuals, households and firms.[1] To get comprehensive data on construction firms and their workers, the core of our data comes from the Employer Monthly Schedule (EMS), which shows all employer-employee relationships. The EMS is derived

[1] See the disclaimer at the front of this paper for information on the conditions of access. The analysis in this paper uses the 20141205 archive of the IDI.

from tax data; each month all employers must file a return with Inland Revenue showing the employees working at the firm that month, the wages paid to them, and the tax deducted.

We use the work of Fabling and Maré (2015a) to identify individuals who are working proprietors at a firm. An individual is counted as a working proprietor if she: pays herself in the EMS (the payer and payee identifiers are the same); reports self-employment income in the IR3 tax form; reports a share of partnership income in the IR7P tax form; or is a company owner receiving payment in the IR4S tax form. Working proprietor relationships are assumed to be permanent, though the labour input from a working proprietor can be zero in a particular year. This identification allows us to separately consider the movements of employees and working proprietors at construction firms. This is important because a large proportion of construction firms in New Zealand are working-proprietor-only firms, and working proprietor relationships may differ on important dimensions compared to employee relationships with firms.

Fabling and Maré (2015a) also provide a measure of employee full-time equivalent (FTE) labour. These measures tend to overestimate true labour input, because they identify FTE as less than 1 only if an employee's income is less than a full-time worker would make on the minimum wage. Despite this, it is better than a simple headcount measure and is the best available labour measure in the IDI.

To these core data we link in numerous other data sources from the IDI, to gain more information on firms and their workers. This is outlined below.

3.1 Worker characteristics

Basic demographic information on employees and working proprietors comes from the IDI's core demographic table, which uses various sources for accuracy.[2] From this, we capture each worker's age.

We also glean information on whether a worker was recently engaged in formal on-the-job training for trade jobs and apprenticeships. In New Zealand, Industry Training Organisations (ITOs) arrange industry training by working with tertiary education providers. The IDI has comprehensive ITO training data from 2003, showing which individuals were engaged in industry training in a given year and which ITO organised the training.

Further information on education comes from the Ministry of Education tertiary education data in the IDI. These data show qualification enrolments and completions (from 1994), as well as course enrolments (from 2001). In documenting the history of construction workers, we simply classify a person as engaging in tertiary study if she studied at least half a full-time equivalent year (0.5 EFTS).

Customs data in the IDI show all border movements into and out of the country, and so allow us to document overseas spells. In documenting the history of construction workers, we

[2] This table is called 'data.personal_detail' in the IDI.

classify a person as overseas if he spent at least half the year overseas. Visa data show all visas that were approved, as well as the type of visa. This allows is to identify which workers in construction are recent migrants, and whether they are here on a work visa or a resident visa.

Finally, we use the analysis and data from Maré and Hyslop (2006) and Maré, Hyslop and Fabling (2016) to get measures of observed and unobserved skills for the employees in our data. These come from regressions at the year-job level, where the dependent variable is an employee's log of earnings and the covariates are a set of worker fixed effects; a set of firm fixed effects; and flexible controls for gender-year specific age profiles of earnings. Hence a worker fixed effect represents the portable wage premium wherever a person works, and so constitute a data-driven approach to measuring unobserved skill levels, while the gender-year specific age profiles provide observed measures of skills. These are an important alternative to looking at qualifications, both because qualifications data in the IDI is not comprehensive and because many differences in skill sets between individuals are not captured by differences in qualifications. A person who is a working proprietor can still have a worker fixed effect, if he ever works as an employee for another firm. We do not focus on the skills of working proprietors, but we do consider separately the average skills of new employees and new working proprietors to a firm.

3.2 Firm characteristics

Data on firm characteristics come from the Longitudinal Business Database (LBD), a component of the IDI which contains a variety of tax, administrative, and survey data on all economically active firms in New Zealand.[3] We use the permanent firm identifiers created by Fabling (2011) to repair broken firm identifiers, which ensures we can track the characteristics and workers of the same firm over time.

Most importantly for this study, each firm in the LBD is assigned a predominant industry, using Australia and New Zealand Industry Classification (ANZSIC) 2006 codes. These allow us to identify construction firms, as well as worker flows between and within industries. We assign to each firm a permanent industry code, calculated as a firm's industry with the greatest share of employee-months.

We identify entrants and exiters by observing employment data over time in the IDI. A firm is an entrant if it had no labour input (either employees or working proprietors) in the previous year and is an exiter if it has no labour input in the following year. This classification is missing in the first year of our data (the year ending March 2000), but otherwise allows us to examine the characteristics of entrant construction firms and where their employees come from.

[3] See Fabling and Sanderson (2016) for details on Statistics NZ's criteria for an enterprise to be considered economically active.

To explore the productivity of firms, we use the productivity dataset created by Fabling and Maré (2015b). They use survey and administrative data for firms in the measured sector to calculate firms' real gross output, capital services, intermediate materials, and labour input. Real output, capital, and intermediate materials are measured by deflating dollar amounts captured in the LBD. The production dataset is not comprehensive, because of missing data and restrictions to ensure consistency and accuracy; firms with useable production data account for 62 percent of total gross output across all industries that are covered by production data. Nonetheless, the productivity coverage is substantial, and allows us to examine the productivity of firms that workers move between. We warn that the labour and capital measures are less reliable for working-proprietor firms than for employing firms (see Fabling and Maré 2015b for details).

In addition to measuring current firm productivity, we use this data to measure knowledge flows from firm to firm. We do this by looking at the productivity of new workers' previous firms, as detailed in Section 5.

In part of our analysis we supplement the above administrative data with the 2005, 2007, 2009, and 2011 Business Operations Surveys (BOS). These surveys, run by Statistics New Zealand and targeted at firms with six or more employees, include questions on firms' sources of new ideas, which we use to corroborate our measures of knowledge flows.

3.3 Sample selection

The broadest analytic sample in this paper is all construction firms in the LBD that have labour input in a given year, for the period 2001-2013. For many descriptive statistics and regressions we limit this to firms in the period 2003-2012, to use firm productivity data and capture the job history of workers new to a firm.

In our productivity analysis, in Section 5, we are limited to firms with useable production data. This decreases the number of firm-year observations from around 550,000 to 360,000 over 2001-2012. As shown by Fabling and Maré (2015b), firms with useable production data in the LBD account for around 60 percent of total industry income. In the year ending March 2012, the specific proportions for construction were: 58 percent for 'building construction', 72 percent for 'heavy and civil engineering construction', and 50 percent for 'construction services'. Firms without production data tend to be small, though we cannot say anything about the productivity of firms for whom we lack production data.

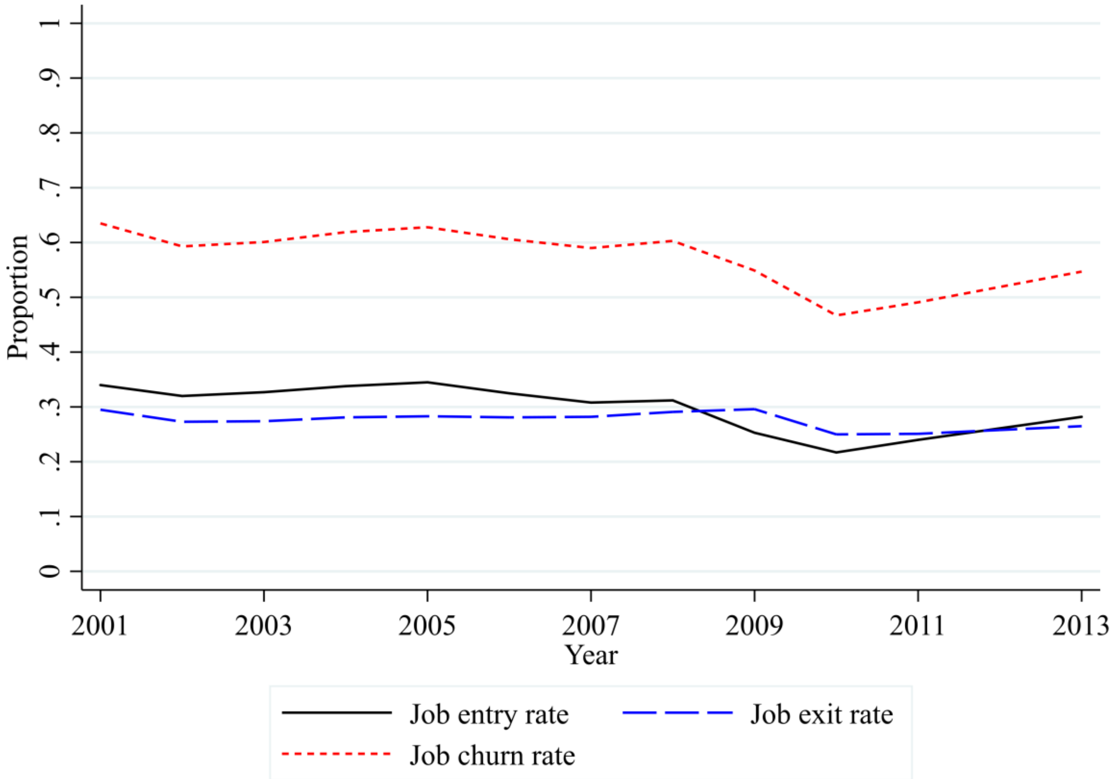
4 Descriptive statistics

4.1 Importance of new labour in construction

If workers new to a firm bring knowledge and improve productivity, then we would expect new labour to have a noticeable presence at the industry and firm level. This subsection documents job churn and the distribution of new labour for firms in construction. Figure 1 shows the job entry, exit, and churn rates over 2001-2013 for workers in construction, whether they are employees or working proprietors. A new (dying) job is defined as the first (last) job seen between an individual and a firm in our data, so that the job entry rate is the proportion of jobs that are new jobs, the job exit rate is the proportion of jobs that are dying jobs, and the job churn rate is the sum of the job entry rate and the job exit rate. The job churn rate is large; in most years around 60 percent of jobs either never existed in the past, or will not exist again in the future. This drops to just under 50 percent in the wake of the global financial crisis, consistent with the general finding that job churn is procyclical (Lazear and Spletzer 2012, Fabling and Maré 2012, Bjelland et al. 2011).[4] Figure 1 also shows that the job entry rate was a few percentage points higher than the job exit rate in the years prior to the Global Financial Crisis (GFC), peaking at 35 percent in the year ending March 2005. Because the job entry rate was higher, there was growth in the number of construction jobs from 2001-2008. After the GFC the exit rate is higher, showing a decline in construction jobs, though the two rates had converged by 2012.

[4] The pattern is similar when defining a new job as a relationship that did not exist the previous year, and an exiting job as one that does not exist the following year.

Figure 1: Job churn in construction

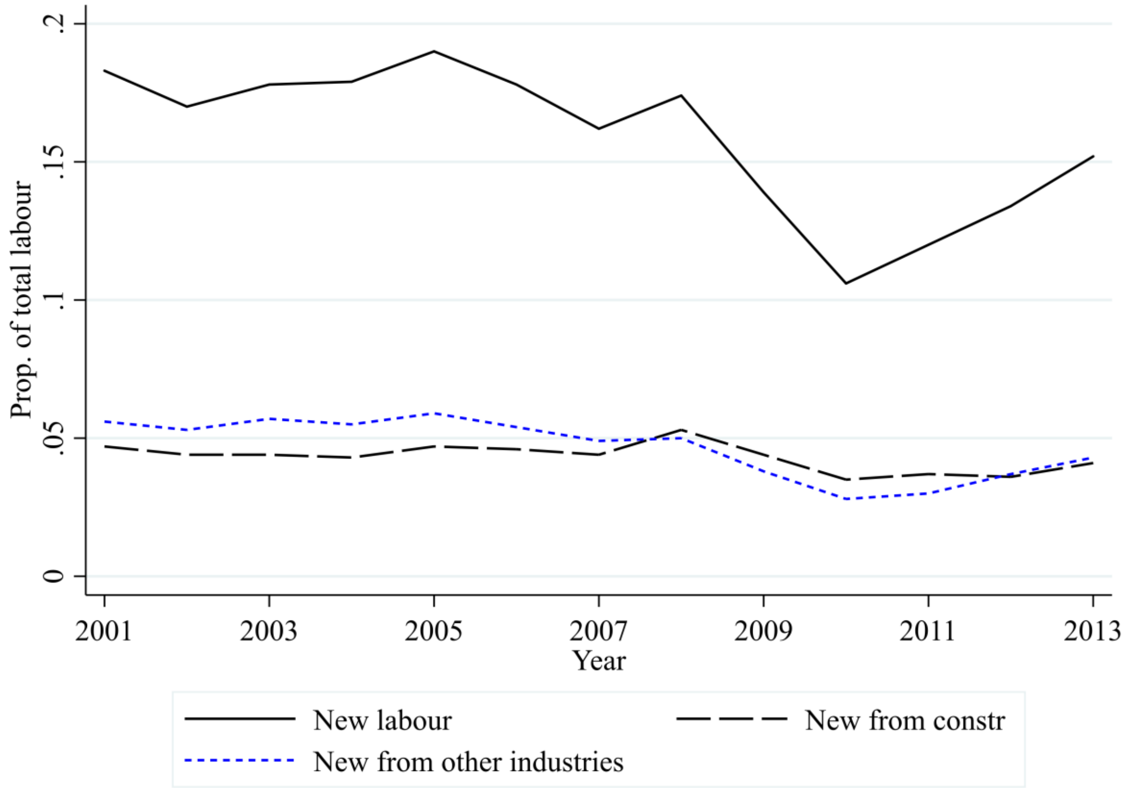


Notes: The job entry rate is the proportion of all construction jobs that are new. The job exit rate is the proportion of all construction jobs that are ending and will not exist again. The job churn rate is the sum of the entry and exit rates.

Figure 2 further documents the importance of workers who are new to firms, showing that the proportion of labour in construction that is new varies from 19 percent (in 2005) to around 10 percent (2010). Though these numbers are large, they are smaller than the total job churn rate in because small amounts of labour underlie many new jobs (e.g. jobs where the person works for only a few weeks). We also split new labour into new labour coming from construction, new labour coming from other industries, and new labour that was not in the job data in the previous year (the left out category, not graphed). A person's labour 'from construction' is calculated by weighting her current labour input by her labour input at construction firms the previous year. For example, if someone works 0.5 FTE this year, and worked 0.5 FTE in construction the previous year, then she contributes 0.25 FTE from construction. Labour from other industries is calculated analogously.

In most years, around five percent of all labour comes from new jobs where the worker was in construction the previous year. A similar rate holds for labour from other industries. These patterns are similar when looking at employee FTE and working proprietor labour separately, as shown in Appendix Figure 1 and Appendix Figure 2. New labour makes up a small but important proportion of the industry's labour.

Figure 2: Proportion of labour in construction that is new



Notes: New labour includes both employee labour (FTE) and working proprietor labour. New labour from a given area (construction or other industries) is calculated as a worker's current labour input multiplied by the worker's total labour input last year in that area.

4.2 Importance of new labour at the firm level

The top panel of Table 1 shows the distribution of labour new to a firm (new employee FTE + new working proprietor labour) scaled by firm size, across all firms in construction over the period 2003-2014. The average firm-year in our data has new labour that makes up 17 percent of its total labour, while the corresponding values for new labour from construction and other industries are five and four percent. Also note the distribution of firm size for construction firms; the median value is 1, the 75th percentile is 2 and the 90th percentile is 4.8, showing the prevalence of small firms in the industry.

When restricting attention to firms with any new labour in a year, the average firm has 47 percent new labour, though only around 30 percent this new labour comes from construction (making up 14 percent of total labour).

The third panel shows that employing firms tend to have proportionally more new labour than working-proprietor-only firms, as the summary statistics are larger than for the first panel including all construction firms. This is supported by Appendix Figure 1 and Appendix Figure 2, which show that construction employee labour is more likely than working proprietor labour to be new.

Finally, the fourth and fifth panels limit the sample to entrants and exiters, respectively. Some entrant firms have old labour input because we define entrants as firms without any labour input in the previous year. That is, a firm could enter the market and employ a builder, exit the market the following year, and re-enter the year after and employ the same builder. This last year would count as an entrant firm with some labour that is not new. Interestingly, the mean of 0.80 means the average entrant firm has 20 percent of its workforce made of up those who worked for the firm two or more years ago. Entrants also source proportionally more of their new labour from construction than other industries; the mean of new labour from construction is 27 percent while the mean of new labour from other industries is only 19 percent, and the 75th percentile value is nearly twice as large (53 percent versus 24 percent). This pattern does not hold for all firms or exiters, suggesting that knowledge flows may play an important role in entrant firms.

Table 1: Distribution of firms' new labour in construction

	Mean	Median	75th pctile	90th pctile	Observation count
All firms					
New labour/firm size	0.17	0	0.15	1	549,687
New labour from constr/firm size	0.05	0	0	0.08	549,687
New labour from other industries/firm size	0.04	0	0	0.09	549,687
Firm size	3.0	1.0	2.0	4.8	549,687
All firms with new labour > 0					
New labour/firm size	0.47	0.29	1	1	202,245
New labour from constr/firm size	0.14	0	0.10	0.56	202,245
New labour from other industries/firm size	0.12	0.02	0.11	0.36	202,245
Employing firms only					
New labour/firm size	0.22	0.08	0.28	1	238,362
New labour from constr/firm size	0.06	0	0.02	0.15	238,362
New labour from other industries/firm size	0.06	0	0.05	0.16	238,362
Entrants only					
New labour/firm size	0.80	1	1	1	78,786
New labour from constr/firm size	0.27	0	0.53	1	78,786
New labour from other industries/firm size	0.19	0	0.24	0.85	78,786
Exiters only					
New labour/firm size	0.20	0	0.07	1	76,743
New labour from constr/firm size	0.05	0	0	0.02	76,743
New labour from other industries/firm size	0.05	0	0	0.05	76,743

Notes: For the period 2001-2012. Some entrant firms have non-new labour because we define entrants as firms that were not active the previous year, meaning they may have employed two or more years ago.

Because we are interested in knowledge flows from firm to firm, it is important to know workers' labour market involvement in previous years. If an employee worked for only a week at another construction firm, there is little chance of her bringing useful knowledge from that job to her new job. If an employee worked full time for the past two years, she is more likely to transfer valuable knowledge.

Table 2 explores workers' past labour market involvement, by showing the distribution of previous labour among workers (employees or working proprietors) at new construction jobs. We show statistics separately for past FTE as an employee and past labour input as a working proprietor because in our regression analysis we consider separately productivity transfer from employees and productivity transfer from working proprietors.

From the first panel of Table 2, the average worker at a new construction job worked a yearly average of 0.16 FTE in construction over the past two years, and 0.25 FTE in other industries. Very few new workers have a history as a working proprietor; the 90th percentile value is zero for past working proprietor labour in construction and other industries. However, the third panel shows that the average working proprietor in a new working proprietor job had over twice as much presence in construction as in other industries (0.59 versus 0.28 working proprietor labour). Consistent with Table 1, we also see that entrant firms source proportionally more of their new labour from construction; the gap between past worker involvement in construction and other industries disappears in the fourth panel, and even reverses when considering the 90th percentile value of past employee labour (0.83 FTE in construction versus 0.65 FTE in other industries).

Together, Table 1 and Table 2 show that an important proportion of construction firms' labour is new, though there are also many firms operating with no new labour; that although new labour from construction is noticeable, it tends to be smaller than the amount of labour coming from all other industries combined and labour coming from outside the labour market; and that entrants tend to source proportionally more of their new labour from construction. This raises the question – despite the modest presence of new labour documented in this section, is new labour important to firm productivity?[5] We address this question rigorously in Section 5.

[5] These statistics are similar when limited to firms appearing in our regression sample (that is, firms with production data and that appear in at least four years).

Table 2: Distribution of previous labour among workers at new jobs

	Mean	Median	75th pctile	90th pctile	Observation count
All new employees & WPs in construction					
Avg. yearly FTE in constr. over past 2 yrs	0.16	0	0.14	0.80	660,867
Avg. yearly FTE in other industries over past 2 yrs	0.25	0.04	0.43	0.90	660,867
Avg. yearly WP labour in constr. over past 2 yrs	0.01	0	0	0	660,867
Avg. yearly WP labour in other industries over past 2 yrs	0.01	0	0	0	660,867
All new employees with employee FTE in last 2 yrs					
Avg. yearly FTE in constr. over past 2 yrs	0.22	0	0.36	0.93	488,226
Avg. yearly FTE in other industries over past 2 yrs	0.34	0.19	0.62	0.96	488,226
All new WPs with WP labour in last 2 yrs					
Avg. yearly WP labour in constr. over past 2 yrs	0.59	0.50	1	1	15,492
Avg. yearly WP labour in other industries over past 2 yrs	0.28	0	0.50	1	15,492
All new employees & WPs in new construction firms					
Avg. yearly FTE in constr. over past 2 yrs	0.15	0	0.07	0.81	122,046
Avg. yearly FTE in other industries over past 2 yrs	0.15	0	0.13	0.65	122,046
Avg. yearly WP labour in constr. over past 2 yrs	0.06	0	0	0	122,046
Avg. yearly WP labour in other industries over past 2 yrs	0.03	0	0	0	122,046
All new employees & WPs in exiting construction firms					
Avg. yearly FTE in constr. over past 2 yrs	0.11	0	0.02	0.52	34,527
Avg. yearly FTE in other industries over past 2 yrs	0.17	0	0.23	0.70	34,527
Avg. yearly WP labour in constr. over past 2 yrs	0.04	0	0	0	34,527
Avg. yearly WP labour in other industries over past 2 yrs	0.02	0	0	0	34,527

Notes: For the period 2003-2012. Previous FTE in construction or other industries is calculated as the current-FTE-weighted average of past FTE. For example, an individual who is new to a firm and works 0.5 FTE, and who worked full time in construction in the last two years, will have an average of 0.5. Past working proprietor labour is calculated with analogous weighting.

4.3 History of workers in construction

This section documents the history of employees and working proprietors at new jobs in construction. The first column of Table 3 starts with people who were working substantially (any working proprietor labour input or at least 0.25 FTE) in construction in given year and shows what they did the previous year. Around two-thirds of construction workers worked substantially for the same firm in the previous year, six percent worked at a different continuing construction firm (neither entering nor exiting), and eight percent worked at a non-construction firm. The two other substantial categories are: miscellaneous work, meaning the person worked at least 0.5 FTE over the year but not enough in one firm to fall in to the earlier categories; and miscellaneous, meaning the person did not fall under any earlier category.

The second and third columns repeat this but consider employees and working proprietors separately. Employees are 13 percentage points less likely than working proprietors to work for the same firm, and twice as likely to work at a different continuing construction firm (7 percent versus 3 percent). These differences in activity highlight the importance of considering employees and working proprietors separately; in addition to the fact that they have different roles and knowledge about the firm, employee flows between firms are more prevalent.

The fourth column of Table 3 considers only workers new to a construction firm and working at least 0.25 FTE for that firm. When excluding the 'working for the same firm' category for comparability, these new workers are disproportionately likely to be working at a non-construction firm (29 percent versus 25 percent for all workers); more likely to have been school age or overseas; and much less likely to be engaged in miscellaneous work across a number of firms (4 percent versus 17 percent for all workers). So although workers who are new to a firm are more likely to come from outside the labour market, substantial numbers still come from other firms, raising the prospect of knowledge flowing through these new workers.

The fifth column considers only new workers at entrant firms. Compared with new workers generally, we see entrant workers are more likely to come from an exiting construction firm (8 percent vs. 4 percent); are less likely to come from a firm in another industry (22 percent vs. 29 percent); are less likely to have been younger than 18 (1 percent versus 6 percent); and are particularly likely to come from unemployment or from outside the labour market (36 percent versus 24 percent). Hence it appears entrant workers tend to be older, more tied to construction, and less tied to other industries.

Finally, Appendix Table 1 replicates Table 3 but presents statistics separately for the three sub-industries of construction, and only for workers at firms with production data in the fourth column. Results are similar, with little difference in worker-history across sub-industry or production-data status.

Table 3: Last year's activity for those currently working in construction

Sample included:	All workers	Employees	Working proprietors	New workers	Workers at entrant firms
Working for the same firm	67%	63%	76%	0%	0%
Working at different constr. continuing firm	6%	7%	3%	22%	23%
Working at different constr. exiting firm	1%	2%	1%	4%	8%
Working at different constr. entering firm	0%	0%	0%	1%	1%
Working at non-constr. firm	8%	10%	4%	29%	22%
Engaged in tertiary study	1%	1%	0%	3%	2%
School age (under 18)	2%	2%	0%	6%	1%
Overseas	2%	2%	0%	7%	2%
Misc. work (at least 0.5 FTE total)	6%	5%	8%	4%	4%
Misc.	7%	7%	8%	24%	36%

Notes: For the period 2003-2012. An individual counts as working for a firm if she is either a working proprietor or works at least 0.25 FTE for that firm over the year.

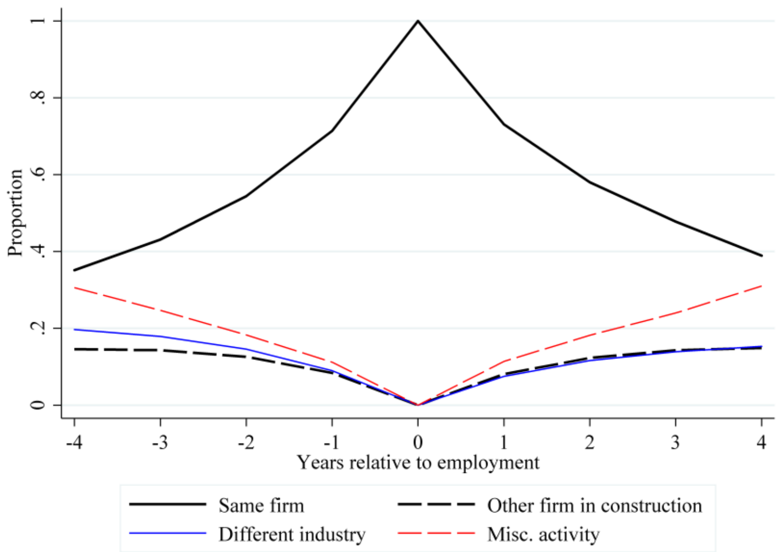
Panel (a) of Figure 3 complements Table 3 by showing the 4-year history and future of all people working in construction between 2005 and 2010. For ease-of-viewing we collapse the ten categories into four: working at the same firm, working at another construction firm, working at a non-construction firm, and miscellaneous. This further highlights the dynamism of the labour market in construction; among those employed, fewer than 40 percent of people held the same job four years prior and only around 40 percent held the same job four years after.

Interestingly, the second most common category is the miscellaneous omitted group. This means that many current workers in construction have pasts and futures that involve some combination of education, overseas travel, several part-time jobs with less than 0.25 FTE worked at each one, and other activities.

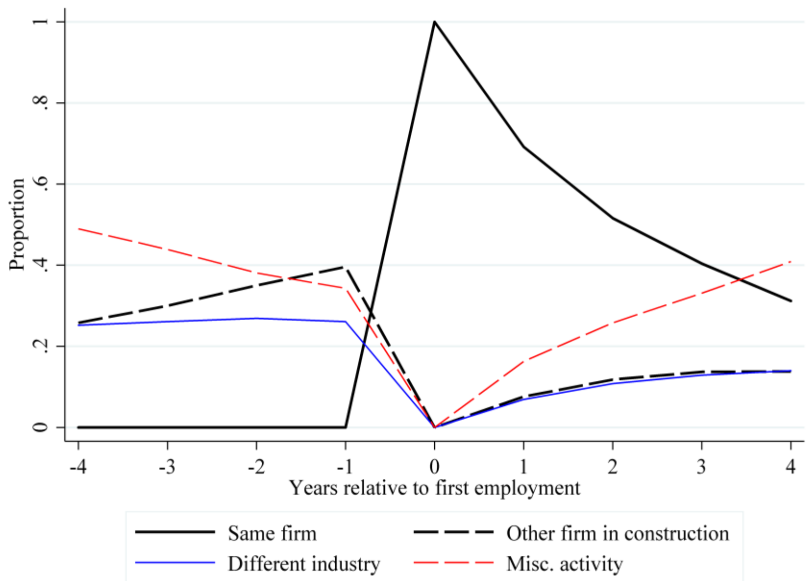
Panel (b) replicates the above for new workers at entrant firms. A new worker cannot have worked at the same entrant firm in previous years, and so the remaining three categories have higher proportions mechanically. However, note that new entrant workers are especially likely to come from other construction firms; in the pre-period the proportion coming from construction diverges from the proportion coming from another industry, while the pattern is the opposite in Panel (a). This pattern suggests one reason entrant firms may be more productive – they source their labour from other construction firms. We explore this hypothesis statistically in Section 5.

Figure 3: Past and future work of construction workers

(a) All workers in construction



(b) All new workers in construction entrant firms



Notes: Pooled across cohorts of construction workers from 2005-2010. A person must work at least 0.25 FTE (or contribute any working proprietor labour) for a firm to be counted as working for that firm. When a person works multiple jobs, we consider only the primary job with the highest yearly earnings.

4.4 Phoenix firms in construction

One additional phenomenon related to firm churn is the birth of so-called 'phoenix' firms. These are firms that 'rise from the dust' of previously exiting firms, and so are experienced firms that appear new to observers. A change to the 1993 Companies Act in November 2007 requires that a director of a failed company must not, for five years after liquidation:[6]

1. Be a director of a phoenix company
2. Be directly or indirectly involved in the promotion, formation, or management of a phoenix company
3. Be directly or indirectly involved in the running of a business with the same/similar name as the failed company

In the above wording, a phoenix company refers to a company with a similar name or trading name as a company in liquidation.[7] An exception to the above is if the phoenix firm buys the insolvent firm from the liquidator/receiver and tells all creditors of the failing firm, or if the director gets court approval.

Hence in late 2007 it became much more difficult to form a phoenix firm with a similar name to the failing firm. The purpose of the law change was to ensure that creditors are not misled about the people running certain companies who may have a bad history. However, note that the law does not ban the formation of phoenix firms; directors can revive a firm that is fundamentally the same but under a different name, or can revive a firm using one of the exceptions listed above.

Using the comprehensive Longitudinal Business Database (LBD), we attempted to look at the prevalence of phoenix firms in construction compared with other industries, and for any structural break after the law change in late 2007. We attempted to identify phoenix firms by using the repaired firm-identifier links created by Fabling (2009). Essentially, a firm in the LBD may cease in year *t*, with another firm entering in year *t+1* as a different legal entity, despite the two firms being economically the same. Fabling (2009) uses the work done by Statistics NZ to repair broken plant identifiers, and extends this to repair broken firm identifiers.

However, we learnt this strategy is flawed and cannot accurately identify phoenix firms. The main issue is that the repaired links, intended for a different purpose, ignore firms that take more than a month to become a different legal entity. This is more likely to reflect a change in legal status than insolvency and resurrection.

When looking at the repaired links, the construction industry is on the higher end, with around 0.7 percent of firm-year observations. Several important industries have larger proportions: manufacturing (1.1 percent), retail (1.2 percent) and accommodation/food services (2.1 percent). We also found a general downward trend over time, particularly for construction which peaks around the law change and declines afterward. However, this does not constitute any real evidence of an impact of the law change, because of our inability to properly identify phoenix firms.

[6] See Section 386A of the Companies Act 1993 for the specific wording: http://www.legislation.govt.nz/act/public/1993/0105/latest/DLM323263.html
[7] https://www.mvp.co.nz/mcdonald-vague-articles/phoenix-companies-what-exactly-are-the-rules-here

4.5 Entrants differentiated by length of survival

Parts of our analysis in Section 5 relate to entrants and firm performance over time. In this section we explore whether all entrants are alike, or whether entrants who last only a short time are fundamentally different.

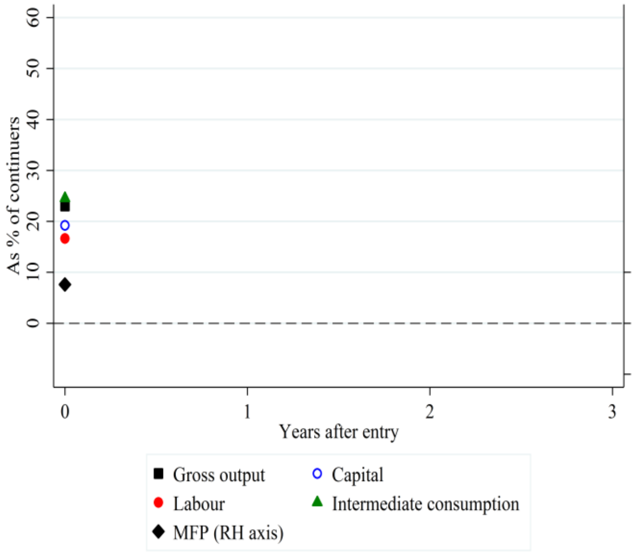
Figure 4 explores this by graphing the average output, inputs (capital, labour, and intermediate materials), and multi-factor productivity (MFP) of entrants relative to continuers who existed in the prior year. This is pooled for all entrant cohorts over 2001-2009, and shown separately for entrants who survive only one year (panel a); entrants who survive two years (panel b); entrants who survive three years (panel c); and entrants who survive four or more years (panel d). Note that average output and inputs are shown as a proportion of the average for continuers on the left-hand axis, while MFP is shown relative to continuers on the right-hand axis. Also note that average inputs and outputs for the first and last years will be mechanically smaller, as many firms enter or exit part way through the year.

Figure 4 holds several lessons. Entrants who exist for only a short period of time seem inherently different from those who enter and stay around. They start with less output and inputs than long-surviving entrants, and output and inputs decrease over time for entrants lasting only two or three years. In contrast, average output and inputs increase for surviving entrants from 30-40 percent of continuers to 50-60 percent after three years. In addition, the level and dynamics of productivity differ for different types of entrant; entrants lasting only one year are around 8 percent more productive than continuers, perhaps due to the low levels of inputs used. Entrants lasting two or three years tend to be more productive at first, but experience declining productivity prior to exiting. In contrast, surviving entrants tend to increase in productivity over time, but start at a lower level of productivity compared with transitory entrants.

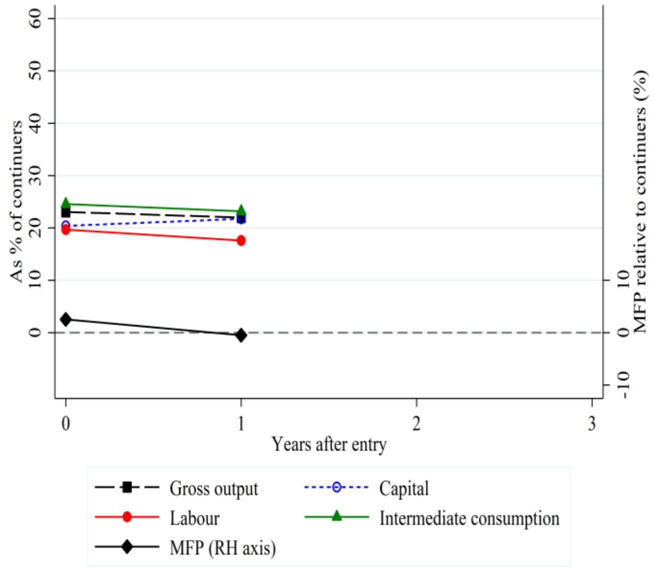
The patterns in Figure 4 highlight the danger of treating all entrants alike when looking at the level and dynamics of productivity. In particular, the finding that firms in their first year have higher productivity than ongoing firms could be associated to a significant extent with the performance of short-lived firms. Since such firms seem to be different from firms that persist, and, by definition, transitory firms do not have a lasting impact on overall industry productivity, in Section 5 we limit our analysis to firms appearing at least four times over the period 2001-2012. We believe that conducting the analysis on this basis makes its conclusions more robust with respect to important contributors to industry productivity.

Figure 4: Average inputs & outputs of entrants relative to continuers, by length of survival

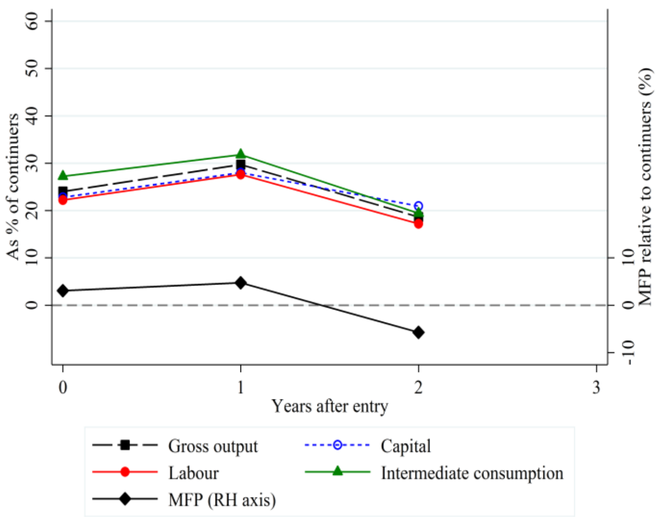
(a) Entrants lasting 1 year



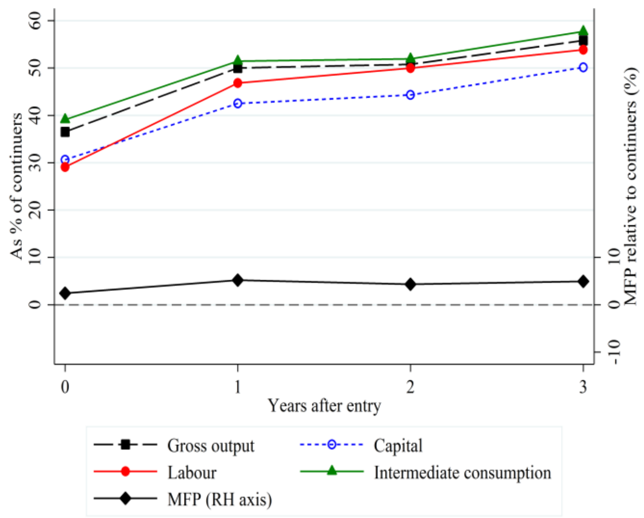
(b) Entrants lasting 2 years



(c) Entrants lasting 3 years



(d) Entrants lasting 4+ years



Notes: For entry cohorts pooled over the period 2001-2009. The reference group of continuers consists of all firms who existed in the previous year. For example, average inputs, outputs and MFP for the 2001 entrants are compared to the average for firms that existed in 2000, and over the subsequent three years (2002-2004).

5 Results

Our framework for looking at productivity is the production function, which models the output of a firm as a mathematical function of the standard inputs used (capital, labour, and intermediate consumption) as well as extra 'augmenting' variables. These extra variables are interpreted as observable firm attributes that are associated with a premium or deficit to productivity while holding constant traditionally measured inputs and other observable factors. In some cases, these augmenting variables are simply 'controls' for firm attributes that are known to be associated with differences in measured productivity; including these in the regressions protects against possibly confounding effects on productivity. An example of an augmenting variable of this type is a dummy variable for the firm operating in Canterbury in the post-earthquake period. The deviations from market equilibrium associated with the rebuild could distort apparent productivity, so we include this variable to remove such effects.

Other augmenting variables capture an association with productivity that we wish to understand. In Section 5.2 we especially focus on augmenting variables that measure the previous productivity of new workers' previous firms. By 'augmenting' the production function with these variables, we can measure the extent to which, holding all other observable variables constant, employing workers from other productive firms is associated with higher productivity for the new employer.[8]

We hence measure and explain multi-factor productivity (MFP), which captures how well firms turn multiple inputs into output. This is preferable to looking only at partial productivity measures such as labour productivity, because a firm could have high labour productivity due to being capital intensive, and yet might not be productive when accounting for the amount of capital used. For a more detailed exposition of productivity and its measurement see Jaffe et al. (2016) and the references within.

Throughout this section we limit our sample to construction firms that appear at least four times between 2001 and 2012, as discussed and justified in Section 4.5.[9]

5.1 Firm productivity and labour movement: overall differences in performance

As motivation for the more structured statistical analysis in the following section, Table 4 groups firms based on whether they gained labour from or lost labour to a particular source, and shows

[8] We could also model productivity transfer using the effective labour input framework of Hellerstein et al. (1999), where different types of labour have differing marginal products. Within this framework, new labour from productive firms could be considered its own category, contributing to a firm's effective labour input at a rate that is different from that of other workers. However, the downside of this approach is that workers of different types are assumed to interact with the other inputs in the same way, as if more productive workers were the same as other workers but just worked more hours. We find it more plausible to allow different kinds of workers to make all of the firms' inputs more or less productive, which is what is captured by the augmented production function approach.
[9] This drops 2.9 percent of industry output and 8.7 percent of firm-year observations with useable production data. Key regressions exploring knowledge flows in Section 5.2 are similar when relaxing this restriction.

the mean productivity of each group. The MFP residuals in the first two columns come from level 2 industry-specific production functions from the population of construction firms, as in Fabling and Maré (2016b). Also note that a given firm may appear in more than one group – for example, a firm may have gained labour from both exiting construction firms and from miscellaneous sources.

The first takeaway is that firms gaining or losing labour have higher multi-factor productivity than firms with no change, and that this holds regardless of the origin or destination. The opposite is true when looking at labour productivity, suggesting that static firms tend to have higher capital intensity. This may stem from the smaller size of firms that neither gain nor lose workers.

Table 4: Productivity and sources of labour gained/lost

	Mean MFP (Cobb-Douglas)	Mean MFP (Translog)	Mean labour productivity	Observation count
Labour gained this period				
Gained labour from exiting constr firms	0.057	0.047	$85,100	9,537
No new labour from exiting constr firms	-0.008	-0.003	$83,700	310,902
Gained labour from non-exiting constr firms	0.039	0.027	$81,800	48,567
No new labour from non-exiting constr firms	-0.014	-0.006	$84,100	271,875
Gained labour from non-constr firms	0.026	0.016	$80,800	70,941
No new labour from non-constr firms	-0.015	-0.006	$84,600	249,501
Gained labour from misc. sources	0.024	0.015	$80,400	80,946
No new labour from misc. sources	-0.016	-0.007	$85,000	239,493
Labour lost last year				
Lost labour to new-entrant constr firms	0.024	0.009	$82,700	7,470
No lost labour to new-entrant constr firms	-0.009	-0.003	$83,300	285,486
Lost labour to non-entrant constr firms	0.015	0.004	$79,700	38,121
No lost labour to non-entrant constr firms	-0.012	-0.004	$83,800	254,835
Lost labour to non-constr firms	0.010	0.001	$81,400	51,360
No lost labour to non-constr firms	-0.013	-0.003	$83,700	241,599
Lost labour to misc. sources	0.013	0.004	$81,700	62,406
No lost labour to misc. sources	-0.014	-0.004	$83,700	230,550

Notes: Pooled over the period 2001-2012, and limited to firms appearing at least four times. A firm must have at least 0.25 FTE or any working proprietor labour from a given source to be counted as gaining labour from that source. Measured MFP residuals in the first two columns are estimated from population-wide production functions, run separately for each level 2 industries (building construction, heavy & civil engineering construction, and construction services).

Second, the origin is important and the destination less so. Firms that gained some labour from exiting construction firms are, on average, 6.5 percent more productive than firms that did not (or 5.4 percent when looking at translog productivity residuals). This productivity advantage decreases as we consider those gaining labour from non-exiting construction firms (a 5.6

percent premium), those gaining labour from other industries (4.1 percent premium) and those gaining labour from miscellaneous sources (3.9 percent premium). There is less of a pattern in the destination of labour lost the previous year, though looking at Cobb-Douglas productivity residuals suggests the largest productivity premium is to those losing labour to new-entrant construction firms (3.3 percent).[10]

These differences in averages cannot be construed as causal, because firms that gain or lose labour will differ on other important dimensions that are also correlated with productivity. For example, less innovative firms are likely to be less productive and also likely to see less change in employment. However, the statistics do tell us interesting things about the activities of the most productive firms, and suggest that labour market dynamism is important to firm performance.

5.2 Entry and employee movement in the augmented production function

The previous section showed that firms' productivity differs in association with the labour history of their workforce. With the job data in the IDI we can do even more, by looking at the productivity level that prevailed at the firms where workers were previously employed. If workers bring new knowledge with them, we would expect a link between the productivity of a new worker's previous firms and the productivity of the firm gaining the worker. Furthermore, the connection should be greatest when looking at the past productivity of other construction firms, because firms in the same industry are more similar in their basic technologies.

At the same time, we know from our previous work that entrant firms are more productive than ongoing firms. We now explore these two possible effects together in the augmented production function framework.

Our preferred regression takes the following form:

$$y_{jt} = \alpha_0 + \alpha_1 k_{jt} + \alpha_2 l_{jt} + \alpha_3 m_{jt} + \beta prod\_flows_{jt} + \gamma_t + \omega entrant + \delta_j + \eta X_{jt} + \varepsilon_{jt} \qquad (1)$$

where *j* denotes firm and *t* denotes year. The lower-case y, k, l, and m represent the log of gross output, capital, labour and intermediate consumption; *prod_flows* is a vector representing the worker past-productivity variables of interest; the variable *entrant* captures whether firm *j* is a entrant during our data period; γ_t denotes a set of year fixed effects to control for yearly aggregate changes in gross output common to all firms; δ_j denotes a complete set of firm fixed effects, which we include in our preferred specifications; X_{jt} denotes a vector of other firm-year specific variables including indicators for having production data from the Annual Enterprise Survey (typically larger firms), and an indicator for being in Canterbury after the 2011 earthquake. The

[10] These basic patterns also hold when looking separately at the three sub-industries of construction. The largest differences are for building construction (an 8.3 percent premium for firms gaining labour from dying construction firms) and smallest for civil and heavy construction (5.5 percent for the corresponding statistic). These tables, not presented, are available upon request.

error term is ε_{jt} and captures variations in gross output not explained by the model. Hence our coefficient estimates of interest are in the vector β, and capture the associations of workers' past productivity with a firm's current productivity.

Table 5 shows key coefficient estimates from regressions in the form of equation (1), including all of the log input variables and control variables; only the coefficients of interest are reported in the Table. The various columns of Table 5 explore the consequences of including or excluding the firm entry and employee movement effects, and of different ways of handling the effect of the unobserved firm characteristics δj. In the first column, we simply reproduce the previous result that entrant firms have higher productivity than continuing firms. That is, for given inputs and control variables, those firms that are entrants at some point from 2001 and after have 6.1 percent greater real output than those that are not entrants. It is important to emphasize that because the regression variable is 'ever an entrant'--not 'entered this year'--this is a persistent difference between the firms that are observed entering and those that are not. Indeed, as discussed further below, these firms seem to continue to increase their advantage as time goes by.

In the second column, we omit this entrant effect, and introduce a set of variables characterizing the workforce of the firm. The variables capturing new workers' average MFP at previous firms is split into employees and working proprietors, and is a double-FTE weighted measure[11]: first, we weight previous MFP by the FTE worked at that firm, because a worker will transfer less knowledge when only working at a previous firm for a short time. Secondly, we weight these past-productivity measures by the current FTE worked with the firm, because a worker will transfer less knowledge and have less impact when only working at a new job for a short time. Furthermore, the past productivity of new workers is measured over the previous two years to minimise the noisiness, and is scaled by firm size because the flow of one worker is less important to larger firms.[12] In addition to these productivity-transfer variables, we include in the regression a set of dummy variables that simply capture whether the firm in that year had any new workers from various sources. We include these variables to try to distinguish between effects due to knowledge that new workers bring and effects simply associated with factors that drive the hiring of new workers.

In the third column of Table 5, we combine the entrant effect with the effects due to worker influx. Comparing the first three columns demonstrates some basic results. First, the entrant effect and the knowledge transfer effect are both present, and they do not interact

[11] The 'FTE' measure for working proprietors is not an accurate labour-input measure. Anyone receiving self-employed income is given a labour-input measure of 1, and this is scaled by the number of working-proprietor jobs in the case of several self-employment relationships. We also emphasise again that the employee FTE measures tend to overestimate actual labour input, as discussed in the data section. See Fabling and Maré (2015a) for details.

[12] Note that past MFP is measured by the Cobb-Douglas production function residuals of Fabling and Maré (2015b) and are estimated separately for industries roughly corresponding to Statistics New Zealand's ANZSIC 2006 level 2 industries. For construction, there are three level 2 industries: building construction, heavy and civil engineering construction, and construction services.

strongly. That is, the magnitude of each effect is not greatly changed by inclusion of the other effect. Second, there is a clear effect of bringing in workers from productive firms, and the knowledge-transfer interpretation of this effect is strengthened by the fact that the productivity benefit is greater when the previous high-mfp employer was a construction firm.

Because the knowledge-flow variables are weighted by the employees' FTE in both the productivity-transferring firm and the productivity-receiving firm, they can be interpreted as a kind of fractional effectiveness of transfer. That is, the coefficient of .32 in the third column, for example, means that if we consider two construction firms with differing productivity levels, and then imagine hypothetically producing two new firms each of which is constructed by simply transferring all of the employees from one of the original two firms, the difference in productivity between the two new firms would be 38 percent (=exp(0.32)-1) of the difference between the original firms. Of course, in reality, firms will be a mixture of old and new employees. If only half of the employees at the new firms come from other firms, then the effect would be half as large.

The estimate for working proprietor past-productivity in construction is similarly large and statistically significant, though smaller in magnitude. Note also that the corresponding variables for non-construction past productivity are considerably smaller and also statistically insignificant in the case of employee flows. This shows that past productivity matters more when coming from construction, which we believe indicates an impact of knowledge flows for the reasons stated earlier in this section.

Table 5: Knowledge flows and productivity

Dependent variable:	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Change in log gross output**
Ever seen entering (2001 onwards)	0.061***		0.055***		0.015***
	(0.004)		(0.004)		(0.002)
New employee mfp at prev constr firms/firm size		**0.326*** **	**0.320*** **	**0.088** **	**0.112* **
		(0.052)	**(0.052)**	**(0.035)**	**(0.058)**
New employee mfp at prev non-constr firms/firm size		0.020	0.020	-0.039**	-0.042
		(0.024)	(0.024)	(0.019)	(0.053)
New WP mfp as WP at prev constr firms/firm size		**0.128*** **	**0.128*** **	**0.030*** **	**0.096* **
		(0.014)	**(0.014)**	**(0.012)**	**(0.058)**
New WP mfp as WP at prev non-constr firms/firm size		0.074***	0.074***	0.001	0.103***
		(0.025)	(0.025)	(0.014)	(0.035)
Some new employees from constr		0.022***	0.015***	0.010***	0.015***
		(0.003)	(0.003)	(0.002)	(0.002)
Some new employees from other industries		0.022***	0.015***	0.010***	0.023***
		(0.003)	(0.003)	(0.002)	(0.002)
Some new WPs from construction		0.112***	0.090***	0.010*	0.082
		(0.007)	(0.007)	(0.006)	(0.059)
Some new WPs from other industries		0.118***	0.098***	0.020**	0.063**
		(0.012)	(0.012)	(0.010)	(0.019)
Observations	281,379	281,379	281,379	281,379	195,585
Std. deviation of new employees' mfp at construction		0.064	0.064	0.064	0.039
Std. deviation of new WP mfp at construction firms		0.756	0.756	0.756	0.351
R-squared	0.885	0.885	0.886	0.663	0.655
Firm FE	No	No	No	Yes	No
Industries included	All constr with lvl 2 FE	All constr with lvl 2 FE	All constr with lvl 2 FE	All constr	All constr with lvl 2 FE

Notes: All regressions also control for log of capital, labour, and intermediate consumption (levels in columns 1-4 and changes in column 5), year and region fixed effects, and include dummy variables for having production data from AES survey and for being in Canterbury in the post-earthquake period. The sample is limited to firms sized at least 0.5 and appearing at least four times over the period 2003-2012, and is limited to the years 2003-2012. All changes in column 5 are two-year changes. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

Finally, the regression also includes dummy variables for a firm's having any new workers from a given source.[13] The positive estimates suggest that firms with new employees are more productive than firms with a static work force. Note that this effect is diminished (but still present) when the entrant dummy is included in the regression. This makes sense, since entrants by definition have new employees. We interpret this effect as likely reflecting that when unobserved good things happen to a firm, it is likely to grow and it is likely to experience a positive productivity shock. Hence we cannot say anything about causality in this relationship. We believe that the importance of these variables lies mainly in capturing the effect of unobserved good news on both productivity and employment growth, so that the effect associated with employment of people from high productivity firms are less likely to be spurious.

The results in the third column demonstrate an association between the employment of workers taken from high productivity firms and high productivity of the newly-employing firm. We would like to interpret this effect in terms of the employees bringing with them knowledge about high-productivity practices. But another interpretation is that the firms that are able to attract new employees away from high-productivity firms are simply better firms, and so their higher productivity reflects that difference in the innate quality of the firm, not any effect brought by the new workers. That is, the firm characteristics represented by the unobserved δj in Equation (1) may be correlated with the variables capturing worker knowledge flows; in that case our inability to include δj in the regression biases our estimate of the knowledge flow effects.

The fourth and fifth columns of Table 5 deal with this problem in different ways. Column 4 is estimated using firm fixed effects. That is, a separate dummy variable for each firm is included in the regression, in effect estimating δj for every j. This is an appropriate estimation strategy if δj is constant across t for given j.[14] As expected, the result of this estimation approach is to diminish the estimated magnitude of the knowledge transfer effect, but it is still present for both employees and working proprietors coming from previously high-MFP firms. The estimate now suggests that about 8 percent of the difference in productivity between source firms is reflected in the productivity of employee-acquiring firms. Another way to interpret the magnitude is that a standard deviation increase in the productivity of new employees' previous firms is associated with a 0.6 percent increase in productivity (.064 * .088 = .006).

Puzzlingly, there is now a negative and statistically significant effect of hiring workers from high-productivity firms outside of construction. While it is easy to see why knowledge from non-construction firms might not be useful, it is hard to see what it would actually be destructive

[13] Above a threshold of 0.15 FTE worked when looking at new employees.

[14] Note that in the fixed-effects estimation, it is not possible to estimate the effects of variables that do not vary over time for a given firm. Hence this column drops the 'ever an entrant' variable.

of productivity. We suspect that this effect may reflect the productivity consequences of hiring workers with particular industrial backgrounds.

The last column is a 'first difference' regression, where the dependent variable is the change in the log of output rather than the log itself. This approach causes δj to drop out of the equation, eliminating the bias but also discarding a lot of information so that it becomes harder to get precise estimates. This loss of precision is seen in the fact that most of the estimates in the last column are not statistically significant. Most are, however, qualitatively similar to the fixed-effect results, with the exception of the coefficient on previous MFP of working proprietors, which becomes negative (though very imprecisely estimated). One interesting result from the first-difference regression is that the coefficient on 'ever an entrant' is positive and statistically significant. Since the dependent variable in this regression is the change in log output, the coefficient of .015 tells us that these firms see productivity growth over two years that is 1.5 percentage points higher than the other firms. This reinforces the suggestion that these firms are fundamentally different than the pre-existing firms.

Table 6 replicates the main results (columns (3) and (4) of Table 5) separately for the main sub-industries of construction. Note first that in every sub-industry, there is a reasonably large and statistically significant positive effect for the entrant firms; for 'heavy and civil construction' this effect is more than twice as large as for the industry overall. The MFP-transfer results are similar for 'building construction' and 'construction services', but are noisy and imprecisely estimated for 'heavy and civil construction' due to the small number of firms. The 'past-productivity from construction' estimates for 'construction services' are statistically significant and larger in magnitude than the pooled-industry estimates, suggesting knowledge flows are especially important in this sub-industry. Construction services firms tend to be especially small, which amplifies the importance of worker flows to the firm's performance. The patterns are similar for 'building construction', though smaller in magnitude and statistically insignificant in the specification with firm fixed effects.[15]

[15] We also ran regressions estimating the 1-year change in log gross output based on the change in the log of inputs and the level of the past-productivity variables and their associated dummy variables. Estimates, not reported, are similar to our firm-fixed-effects specifications, though slightly smaller in magnitude. The ever-entrant dummy is positive, suggesting much older firms also grow more slowly (1.4 percent less per year for all of construction).

Table 6: Knowledge flows and productivity, by sub-industry

Dependent variable:	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**
New employee mfp at prev constr firms/firm size	**0.239*** (0.064)**	**0.047 (0.051)**	**-0.014 (0.148)**	**-0.107 (0.145)**	**0.418*** (0.081)**	**0.138*** (0.045)**
New employee mfp at prev non-constr firms/firm size	0.027 (0.038)	-0.042 (0.029)	-0.036 (0.162)	-0.123 (0.164)	0.020 (0.031)	-0.037 (0.025)
New WP mfp as WP at prev constr firms/firm size	**0.099*** (0.021)**	**0.023 (0.014)**	**0.164** (0.067)**	**0.081 (0.055)**	**0.149*** (0.018)**	**0.033* (0.017)**
New WP mfp as WP at prev non-constr firms/firm size	0.108*** (0.033)	-0.016 (0.021)	0.052 (0.065)	0.025 (0.024)	0.049*** (0.018)	0.005 (0.017)
Some new employees from constr	0.015*** (0.005)	0.008** (0.004)	-0.016 (0.012)	0.015** (0.007)	0.018*** (0.003)	0.010*** (0.002)
Some new employees from other industries	0.024*** (0.005)	0.009** (0.004)	0.007 (0.012)	0.015 (0.009)	0.009*** (0.003)	0.009*** (0.002)
Some new WPs from construction	0.076*** (0.010)	-0.004 (0.009)	0.164*** (0.034)	0.045* (0.024)	0.091*** (0.009)	0.014* (0.008)
Some new WPs from other industries	0.087*** (0.022)	0.061*** (0.021)	0.125*** (0.048)	0.025 (0.026)	0.102*** (0.014)	0.007 (0.012)
Ever seen entering (2001 onwards)	0.077*** (0.007)		0.131*** (0.022)		0.043*** (0.005)	
Observations	90,690	90,690	8,577	8,577	182,112	182,112
R-squared	0.887	0.682	0.942	0.724	0.877	0.659
Firm FE	No	Yes	No	Yes	No	Yes
Industries included	Building constr	Building constr	Heavy & civil constr	Heavy & civil constr	Constr services	Constr services

Notes: All regressions also control for log of capital, log of labour, log of intermediate materials, year and region fixed effects, and include dummy variables for having production data from AES survey and for being in Canterbury in the post-earthquake period. See further notes in Table 5. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

A separate question is whether our results are driven by employees at high-MFP firms being simply better-trained, better-educated or smarter than those at lower-MFP firms. Under this interpretation, the productivity benefit associated with hiring these people reflects more their innate characteristics than any transfer of MFP-enhancing practices from one firm to another.

Appendix Table 2 suggests that a modest amount of this sorting of the best employees into the best firms does occur in construction. Using the worker and firm fixed effects estimates of Maré, Hyslop and Fabling (2015), it groups firms by whether they are 'good' firms (high-paying regardless of who their employees are) and shows the proportion of their workers who are 'good' (highly paid wherever they work). The Table shows that 'good' firms are somewhat more likely to have 'good' workers, both in terms of employees overall and in terms of new hires, though the differences are not large--just a few percentage points in each case.

To control for whatever amount of employer-employee sorting may be occuring, we can add augmenting variables to the production function that capture employee characteristics. Column (1) of Appendix Table 3 repeats our main specification but controls for the average unobserved and observed skills of a firm's new workers. Unobserved skills are measured with estimated worker fixed effects, while observed skills come from gender-year specific age profiles.[16] The average worker skill variable is positive and statistically significant for new employees, and positive though statistically insignificant for new working proprietors, showing that firms who hire more skilled workers tend to be more productive. Importantly, the addition does not materially change the estimates on the four knowledge-flow variables. Column (2) includes firm fixed effects in our augmented production function. The results are similar to column (4) of Table 5, supporting the knowledge-flow interpretation of the MFP-transfer results.

For robustness, columns (3) and (4) of Appendix Table 3 replicate columns (3) and (4) of Table 5 but weight each firm by its gross output. This approach gives more importance to larger firms, allowing the interpretation of the result for the average unit of output in construction rather than for the average firm. The results are somewhat smaller for the 'past productivity from construction' variables, again suggesting that knowledge flows are less important for larger firms. This holds even after scaling key covariates by firm size.[17]

While the results in Tables 5 and 6 allow entrants to have a different productivity level than other firms, they constrain the MFP-transfer effects to be the same in the two groups. The last column of Appendix Table 3 explores whether knowledge flows matter more for new firms, by limiting the sample to entrants in construction. The regression excludes firm fixed effects

[16] See the data section for more details. We use one skills variable by adding together each person's work fixed effect and each person's predicted benefit to wages because of the gender-year specific age profile. We then standardise this measure before including it in our regression.

[17] We also ran regressions separately for small firms (under the 75^{th} percentile of firm size, which is about 2.2 FTE) and large firms (at and above the 75^{th} percentile of firm size). Our main estimates are positive and statistically significant for small firms, and smaller and insignificant, though still positive, for large firms.

because few firms enter more than once.[18] The estimates for three of the past-productivity variables are slightly larger than the corresponding estimates for all firms in column (3) of Table 5, while the estimate for 'new employees coming from non-construction firms' is twice as large. Overall, the results suggest the phenomenon of knowledge flows is similar in entrant firms.

Finally, Appendix Table 4 replicates columns (3) and (4) of Table 5, for all of construction and the three sub-industries, but uses a different measure of knowledge flows. These new measures consider separately labour from productive and unproductive firms, for construction and other industries. The main patterns are similar, where new employees from productive construction firms matter more than those from productive non-construction firms (though this does not hold for new working proprietors).

5.3 Employee movement and new ideas

We believe that the regression models in the previous section are strongly supportive of the hypothesis that employees from high-MFP firms can to some degree transfer the knowledge underlying that high MFP to other firms when they change jobs. But of course it is hard to know for sure because we do not observe the knowledge transfer itself. To shed some additional light on the issue, Table 7 explores whether our measure of employees' past productivity is associated with firms' reporting new ideas. The dependent variables come from the innovation modules of the 2005-2011 Business Operations Surveys (BOS), and so the regressions are limited to the much smaller sample of construction firms answering these questions. The first column shows that firms with higher employee past-productivity are more likely to report new ideas for innovation from new staff: consider a firm that gains new employees making up half its labour force, where the employees are coming from construction firms ten percent more productive than the industry average. The coefficient of 2.261 means that such a firm is 11 percentage points more likely to report new ideas from new staff, on average and holding all else constant (2.261 * 0.5 * 0.1 = 0.113).

A similarly strong relationship is found when looking at new ideas from firms in the same industry, while estimates are smaller and statistically insignificant when looking at reporting of ideas from old staff and ideas from firms in other industries. This is reassuring, and gives further evidence that our measures of past-productivity are capturing knowledge flows from other firms. When looking at the past productivity of non-construction workers, the coefficient estimates are smaller and statistically insignificant. This suggests that within-industry knowledge flows are especially important, and that part of the mechanism is through innovative ideas and not merely productivity embodied in a worker that will be lost when the worker moves on.[19]

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[18] Although this is possible, because we define entrants as firms with no labour input in the previous year.

[19] Though note that these patterns don't hold when measuring past-productivity as in Appendix Table 4. One interpretation is that our main measure is better, because it correlates with these BOS variables in the

One caveat is that the BOS survey only targets firms with six or more employees. From Table 1, we know that this excludes more than 90 percent of construction firms. Despite this, the last section suggested that the transfer of productivity is stronger in small firms. The patterns in Table 7 may be even stronger if small firms were included in the BOS.

Overall, this section has presented evidence that knowledge flows have a meaningful impact on firm productivity in the construction industry. We cannot refute the possibility that our estimates are too high; firms may especially hire from other productive construction firms when experiencing a boost to productivity for unrelated reasons, and hence cautiously interpret our estimates as upper bounds on the impacts of knowledge flows.[20]

5.4 Firm productivity and new migrant labour

This section explores how firm productivity correlates with the presence of recent migrants at the firm. This is particularly relevant in New Zealand, because the government elected in 2017 is planning to build 100,000 new houses in the coming decade. This will require more people working in the construction industry. Does it matter whether new construction workers are sourced from other industries or from overseas?

Table 8 explores this, by estimating augmented production functions for the construction industry. We include a suite of variables capturing the amount of new labour coming from people with recent work visas[21], recent resident visas, from construction, from other industries, and from unknown sources. These variables are scaled by firm size, because a given amount of new labour is less important to a large firm.

expected ways. But it is also important to maintain some skepticism and remember that our measures are not perfect.

[20] We also added variables capturing the average age of new employees and working proprietors, and the proportion of a firm's labour force with industry training. The unreported results are similar, showing that our estimates are not driven by the age of new workers or their industry training.

[21] We define a visa as 'recent' if it was stamped in the two years prior to the person working at a firm (from the start of the firm's tax year). We also ran regressions where work visas were split into skilled versus non-skilled work visas. Estimates on these variables were noisy, and so we only report estimates where all people with work visas are pooled into one group.

Table 7: Sources of new ideas and employee past-productivity

Dependent variable:	**Any new ideas for innovation from new staff**	**Any new ideas for innovation from old staff**	**Any new ideas for innovation from firms in the same industry**	**Any new ideas for innovation from firms in other industries**
New employee mfp at prev. constr. firms/firm size	**2.261****	**1.085**	**1.957****	**0.489**
	(0.923)	**(0.678)**	**(0.857)**	**(1.318)**
New employee mfp at prev. non-constr. firms/firm size	-0.013	0.458	0.972	-0.183
	(1.017)	(1.042)	(0.849)	(0.746)
Log firm size	0.086***	0.070***	0.027	0.012
	(0.019)	(0.016)	(0.021)	(0.020)
Mean of dependent variable	0.637	0.797	0.413	0.213
Observations	477	477	459	444
R-squared	0.073	0.060	0.052	0.022
Industries included	All constr with lvl 2 FE	All constr with lvl 2 FE	All constr with lvl 2 FE	All constr with lvl 2 FE

Notes: For construction firms in odd-years from 2005 to 2011 appearing in the Business Operations Survey innovation module. All regressions also control for year and region fixed effects. The sample is limited to firms sized at least 0.5. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

The first column is in levels and lacks firm fixed effects. Focusing on the employee variables, the negative estimates on the 'work visa' and 'resident visa' suggest that, on average and holding all else constant, firms with more recent-migrant labour are less productive. The effect is reasonably large--8 to 14 percent less output for a given level of inputs. The second column includes firm fixed effects, to use only the within-firm variation in the dependent and independent variables, and the negative coefficients disappear; they are statistically insignificant, and the 'work visa' estimate is very close to zero. This means that the lower productivity associated with the hiring of immigrant workers is actually connected to the firms that do such hiring, rather than differentially lower productivity in the year that immigrants are hired. The 'from other industries' variable is similarly small and statistically insignificant. Finally, the third column removes the firm fixed effects and looks at the change in productivity, rather than the level of productivity. The estimate for 'work visa' FTE is small and statistically insignificant; the estimate for 'resident visa' FTE is negative and large, though statistically insignificant because the estimate is noisy; and the estimate for 'other industry' FTE is large, positive, and statistically significant.

The basic patterns are somewhat similar for working proprietor labour, though estimates are particularly noisy in the third column.

We emphasise that these regressions cannot tell us the causal effect of new labour on firm productivity, but the correlations are still informative. Over 2003-2012, firms who sourced new labour from recent migrants tended to be less productive, and firms who sourced new labour from construction and other industries tended to be more productive. The fact that the difference goes away after controlling for firm fixed effects suggests that the mechanism at work has to do with the nature of firms that hire immigrants, rather than the productivity performance of new immigrants themselves.[22]

[22] Results are similar when estimated only for the 'building construction' subindustry, although estimates are noisier because there are fewer observations.

Table 8: Firm productivity and new migrant labour

Dependent variable:	**Log gross output**	**Log gross output**	**Change in log gross output**
New FTE employees with work visas/firm size	-0.139**	0.009	0.050
	(0.059)	(0.052)	(0.080)
New FTE employees with resident visas/firm size	-0.083	0.039	0.071
	(0.057)	(0.049)	(0.089)
New FTE employees from construction/firm size	0.057***	0.010	0.064***
	(0.012)	(0.010)	(0.023)
New FTE from other industries/firm size	0.030**	0.007	0.133***
	(0.014)	(0.012)	(0.026)
New FTE from misc sources/firm size	0.033***	0.023***	0.074***
	(0.010)	(0.009)	(0.015)
New WP labour with work visas/firm size	-0.060**	-0.015	0.326
	(0.030)	(0.034)	(0.222)
New WP labour with resident visas/firm size	-0.031**	-0.065***	0.127**
	(0.014)	(0.013)	(0.051)
New WP labour from construction/firm size	0.086***	0.013***	0.188
	(0.006)	(0.005)	(0.151)
New WP labour from other industries/firm size	0.093***	0.017	0.092**
	(0.013)	(0.011)	(0.045)
New WP labour from misc sources/firm size	-0.004	-0.043***	0.031
	(0.004)	(0.004)	(0.019)
Ever seen entering (2001 onwards)	0.056***		0.013***
	(0.004)		(0.002)
Observations	281,379	281,379	195,585
R-squared	0.885	0.670	0.656
Firm FE	No	Yes	No
Industries included	All constr with lvl 2 FE	All constr	All constr with lvl 2 FE

Notes: All regressions also control for log of capital, log of labour, log of intermediate materials (in changes in column (3)), year and region fixed effects, and include dummy variables for having production data from AES survey, and for being in Canterbury in the post-earthquake period. A worker is said to have a visa if the visa was stamped in the two years prior to a firm's tax year. We prioritise resident visas over work visas, so that a person cannot have both in our regressions. The sample is limited to firms sized at least 0.5, and appearing at least four times over the period 2003-2012, and is limited to the years 2003-2012. Changes in column 3 are two-year changes. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

5.5 Dynamics of productivity after entry

Jaffe et al. (2016) found that entrants are more productive than continuing firms, with that productivity advantage being largest in the first year and then declining over the next few years. In Section 4.5 above we suggested that this apparent result may be driven by the measured performance of firms that enter and then quickly disappear. In this section we explore in more detail the dynamics of productivity in the years following entry.

In examining firm productivity over time, we first limit our sample to firms who appear at least four times. This is because Section 4.5 showed that transitory entrants are different from surviving entrants, and that even firms surviving for three years start off with fewer inputs than firms surviving for four or more years. Hence we exclude noisy, transitory firms that rapidly come in and out of existence.

The first column of Table 9[23] presents a regression that is analogous to those in Jaffe et al. (2016); it is an augmented production function with dummies for each of a firm's first 4 years, plus a dummy for its last year. The left-out group, and hence the group against which each of the dummy coefficients is calculated, is all years that are not years 1-4 and are not a final year. The results are similar to those in the previous paper. It shows that the first few years of a firm's existence are comparatively high productivity years. But it is important to think carefully about what these coefficients actually measure. Firms that are not observed as entrants never have an early year observed in our data. So the comparison underlying the coefficients in the first column is between the early years of entrant firms, and a mixture of (a) years 5 and up for entrants, and (b) all years for non-entrants. We know that entrant firms have, on average, higher productivity in all years than non-entrant firms. The existence of this positive effect makes it hard to know in column (1) what is going on between the early years and other years for the entrants themselves.

To unpick this puzzle, columns (2)-(5) of Table 9 are estimating including only those firms that are observed as entrants at some point. This means that the coefficients are not influenced by the overall difference in productivity between the entrant group and the non-entrant group. Column (2) is just like Column (1), but estimated on this smaller sample. We find that the positive and significant coefficient on the first year goes away, suggesting that that result in the first column is dominated by entrants overall being more productive than non-entrants, rather than by what goes on in entrants' first year. But the interpretation of the results in column (2) is still made somewhat murky by the fact that we observe some entrants for 4 years, some for 5, some for 6, etc. The coefficient on year 1 is the average difference between year 1 and all years greater than 4. If firms that appear in the data for different durations differ from each other, those across-firm differences will be affecting the results in column (2) in an unknown way.

[23] We also replicate Table 9 separately for the three main sub-industries of construction. Results, not reported, are qualitatively similar.

Column (3) explores the dynamics further by estimating the model with firm fixed effects. This means that the coefficients for each dummy represent the average difference for the observations in that group between that observation and the mean for the corresponding firm. The coefficient on the first year is now negative and statistically significant. This means that for firms that enter at some point in the observed period, the first year we observe them exhibits about 7 percent lower productivity than the average in the data for that firm. This below-average performance falls to 1-2 percent in years 2-4.

The last two columns of Table 9 test whether inclusion of the MFP-transfer variables discussed in the previous section affects the results regarding entrant productivity dynamics. For the most part, they do not. That is, column (4) is pretty similar to column (2), and column (5) is very similar to column (3). So once again it would seem that the dynamics of entry are real and are not driven primarily by the presence of new employees in entrant firms. Finally, we note that the final year a firm is observed shows productivity consistently about 15 percent below non-exit years, and this estimate is highly robust to the different specifications.

Overall, the dynamics of productivity after entry are complex. The fixed effect for each firm (its overall mean) is estimated, of course, on the data observed. For some firms this is 5 years; for some it is more. For a firm that is in the data for 5 years, we do not know what its firm mean would be if it were around for 10. Ultimately, since we have unbalanced data and we do not know why firms come and go, there are limits to how much we can say about the underlying dynamics. But we can note two strong tendencies, even if we cannot explain them: firms that are observed to enter sometime in the period have persistently higher productivity than non-entrants. And the productivity observed in a firm's first year, for entrants that continue to produce for at least 4 years, is lower than the average productivity eventually observed for the firm. This suggests that the entrants are intrinsically different firms than the non-entrants, and that their superior performance is not an artefact of the start-up situation. Indeed, performance in the first year is systematically below that which surviving entrants eventually achieve.

Table 9: Firms' productivity over time

Dependent variable:	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**
Firm's 1st year	0.037***	-0.002	-0.070***	-0.035***	-0.088***
	(0.005)	(0.006)	(0.007)	(0.006)	(0.008)
Firm's 2nd year	0.061***	0.029***	-0.018***	0.023***	-0.021***
	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)
Firm's 3rd year	0.048***	0.017***	-0.019***	0.016***	-0.020***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Firm's 4th year	0.049***	0.017***	-0.011***	0.018***	-0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firm's final year	-0.155***	-0.145***	-0.129***	-0.145***	-0.130***
	(0.006)	(0.008)	(0.007)	(0.008)	(0.007)
Sample	Firms who appear 4+ times	Ever-entrants who appear 4+ times	Ever-entrants who appear 4+ times	Ever-entrants who appear 4+ times	Ever-entrants who appear 4+ times
Controls for new workers' past productivity	No	No	No	Yes	Yes
Observations	281,379	156,159	156,159	156,159	156,159
R-squared	0.886	0.853	0.665	0.854	0.660
Firm FE	No	No	Yes	No	Yes
Industries included	All constr. with lvl 2 FE	All constr. with lvl 2 FE	All constr.	All constr. with lvl 2 FE	All constr.

Notes: All regressions also control for the log of capital, log of labour, log of intermediate consumption, year and region fixed effects, and include dummy variables for having production data from AES survey and for being in Canterbury in the post-earthquake period. The sample is limited to firms sized at least 0.5, and is limited to the years 2004-2012. Standard errors, in parentheses, are robust and clustered at the firm level. Asterisks denote: *** p<0.01, ** p<0.05, * p<0.10.

6 Summary and discussion

This paper has analysed how the flows of firms into markets, and workers into firms, interacts with the productivity of firms. Jaffe et al. (2016) found that firm churn boosts productivity; we hypothesised that part of this may be due to workers' spreading knowledge between firms and boosting the productivity of entrants. Although international literature suggests firm churn is a sign of a healthy economy, the potential for knowledge flows through workers is especially high in New Zealand's construction industry due to the large number of very small firms.

We have shown that workers regularly change jobs in construction: in most years between 2001 and 2013 around 60 percent of worker-firm pairs either did not previously exist or will not exist the following year. In terms of overall averages, this movement of workers is associated with higher productivity. Firms that gain or lose any labour are more productive than static firms, and firms that gain labour from other construction firms are especially productive.

By looking at the past productivity of new workers' previous firms, we also find evidence that workers transfer productivity when changing firms; the average firm is more productive when more of its labour is made up of new workers who were previously employed at more productive firms. We note that we have not established a causal relationship running from the productivity of previous employers to the productivity of new employers. Comparing the results with and without firm fixed effects suggests that much of the impact is a matching effect--high quality firms attract and employ workers from other high-quality firms. There is, however, a portion of the impact that remains after controlling for this effect, and workers from construction seem to transfer productivity to a much greater extent than workers from other industries. These results do suggest that there is a small but statistically significant effect that can be associated with knowledge flowing from firm to firm through worker flows.

The knowledge-flow interpretation is corroborated by a finding that firms with new employees sourced from high-MFP construction firms are more likely to report getting ideas for innovation from new staff and from other firms in construction, while they are not more likely to report getting innovative ideas from old staff or from outside construction. Further, having new employees from high-MFP firms *outside* construction is not associated with reporting getting new ideas.

We also explored more thoroughly the productivity advantage of entrants, and find a more complex but ultimately more plausible pattern of effects. We show that the relatively large productivity premium in firms' first year reflects mostly that firms observed to enter during this period are systematically and persistently more productive than previously existing firms, combined with the unusually high productivity of firms that appear for just a single year. We cannot explain the high productivity of transitory firms, but suspect that it reflects nonequilibrium behaviour and possibly mismeasurement of inputs in firms that come and go.[24] For these reasons, combined with the fact that by their nature such firms do not have a big impact on overall industry performance, we view this more as an anomaly than an important phenomenon.

Once these effects are accounted for, we find that entrant firms that persist for more than a few years are actually modestly *less* productive in their first year than they later become. We believe that these patterns suggest that entrant firms have intrinsic advantages over previously existing firms, but it does take them a year or more to build their productivity to its true potential.

Finally, we find that less productive firms tend to have more new migrant labour, but that productivity doesn't decrease when a given firm hires more migrants. While these estimates are not causal, they suggest that whether new workers come from overseas or from other industries matters little to firm productivity. This may have relevance to the government's plan to build 100,000 new houses in the next decade, which will boost the size of the industry.

Together, our results confirm that inflows of new firms and movement of employees are important to firm productivity. New firms are more productive than existing firms--briefly and perhaps meaninglessly for those that quickly disappear, but persistently and increasingly for those that do persist. This is in part because entrants enjoy the benefits of knowledge flows from other firms carried by their new employees, but the new employee/knowledge flow effect and the entrant effect are mostly distinct effects--entrants are more productive than can be explained by the previous experience of their new employees, and non-entrants also benefit from knowledge associated with new employees.

Further research could explore whether these relationships hold and are as strong in other industries. Further work could also look at the less productive firms whose existence predates the data period. The implications for policy depend on whether old firms have obsolete technology, have market power and less incentive to innovative, or have simply grown complacent. Finally, it would be interesting to investigate whether these patterns have persisted in more recent years when the industry has been growing rapidly. It is possible that entrants and new employees who are drawn into the industry when demand surges are different in nature from entrants and new employees during more stable periods.

[24] The high productivity of short-lived firms may also reflect high performance of specialized 'firms' that are formed to carry out a single job or project and then dissolved.

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Appendix tables

Appendix Table 1: Last year's activity for constr. workers, by sub-industry and production-data status

Sample included:	All workers, building constr.	All workers, heavy & civil constr.	All workers, constr. Services	All workers in constr. firms with production data
Working for the same firm	67%	68%	67%	67%
Working at different constr. continuing firm	6%	6%	5%	6%
Working at different constr. exiting firm	2%	1%	1%	1%
Working at different constr. entering firm	0%	0%	0%	0%
Working at non-constr. firm	7%	10%	8%	8%
Engaged in tertiary study	1%	1%	1%	1%
School age (under 18)	2%	1%	2%	2%
Overseas	2%	2%	2%	2%
Misc. work (at least 0.5 FTE total)	5%	6%	6%	6%
Misc.	8%	5%	8%	7%

Notes: For the period 2003-2014. An individual counts as working for a firm if she is either a working proprietor or works at least 0.25 FTE for that firm over the year.

Appendix Table 2: Positive matching between good workers and good firms

High firm fixed effect (>0)	Prop. of workers with high worker Fes (>0)	Observation count
All workers, unweighted		
0	0.376	1,020,639
1	0.413	1,112,346
All workers, fte-weighted		
0	0.411	1,020,639
1	0.449	1,112,346
New workers, unweighted		
0	0.348	402,180
10	0.376	416,079
New workers, fte-weighted		
0	0.385	402,180
1	0.420	416,079

Notes: This table groups firms by whether they are high-paying firms (high FFE), and then summarises the skill composition of their work force. It includes employees and working proprietors (WPs), with WPs weighted by pseudo-WP labour in the weighted panels. For all construction firms over the period 2001-2012.

Appendix Table 3: Knowledge flows and productivity, extensions and robustness checks

Dependent variable:	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**
Extension/robustness check:	*Control for new-worker skills, without firm FE*	*Control for new-worker skills, with firm FE*	*Weight by gross output, without firm FE*	*Weight by gross output, with firm FE*	*Entrants only, without firm FE*
New employee mfp at prev constr firms/firm size	**0.313***** **(0.052)**	**0.086**** **(0.034)**	**0.224***** **(0.046)**	**0.047** **(0.043)**	**0.318***** **(0.058)**
New employee mfp at prev non-constr firms/firm size	0.019 (0.023)	-0.040** (0.019)	0.094** (0.038)	-0.023 (0.028)	0.055 (0.037)
New WP mfp as WP at prev constr firms/firm size	**0.128***** **(0.014)**	**0.028**** **(0.012)**	**0.112***** **(0.012)**	**0.038**** **(0.015)**	**0.208***** **(0.025)**
New WP mfp as WP at prev non-constr firms/firm size	0.073*** (0.025)	-0.003 (0.013)	0.036* (0.019)	0.027* (0.016)	0.112*** (0.043)
Some new employees from constr	0.001 (0.003)	0.004** (0.002)	-0.025*** (0.008)	-0.002 (0.005)	0.065*** (0.010)
Some new employees from other industries	-0.003 (0.003)	0.003* (0.002)	0.004 (0.008)	0.010** (0.004)	0.052*** (0.011)
Some new WPs from construction	0.090*** (0.007)	0.014** (0.006)	0.017 (0.013)	0.029** (0.012)	0.122*** (0.010)
Some new WPs from other industries	0.100*** (0.012)	0.030*** (0.010)	0.029** (0.013)	0.021* (0.012)	0.127*** (0.017)
Avg. skills of new employees/firm size	0.027*** (0.009)	0.009 (0.007)			
Avg. skills of new working proprietors/firm size	0.010* (0.006)	-0.023*** (0.006)			
Ever seen entering (2001 onwards)	0.053*** (0.004)		0.024 (0.016)		
Observations	281,379	281,379	281,379	281,379	22,203
R-squared	0.887	0.664	0.993	0.998	0.799
Firm FE	No	Yes	No	Yes	No
Industries included	All constr with lvl 2 FE	All construction	All construction	All construction	All constr with lvl 2 FE

Notes: Average new worker skills are fte-weighted, and are measured by worker fixed effects and gender-specific age profile parameters in separate wage regressions. All regressions also control for the log of capital, log of labour, log of intermediate materials, year and region fixed effects, and include dummy variables for having production data from the AES survey and being in Canterbury in the post-earthquake period. See further notes in Table 5.

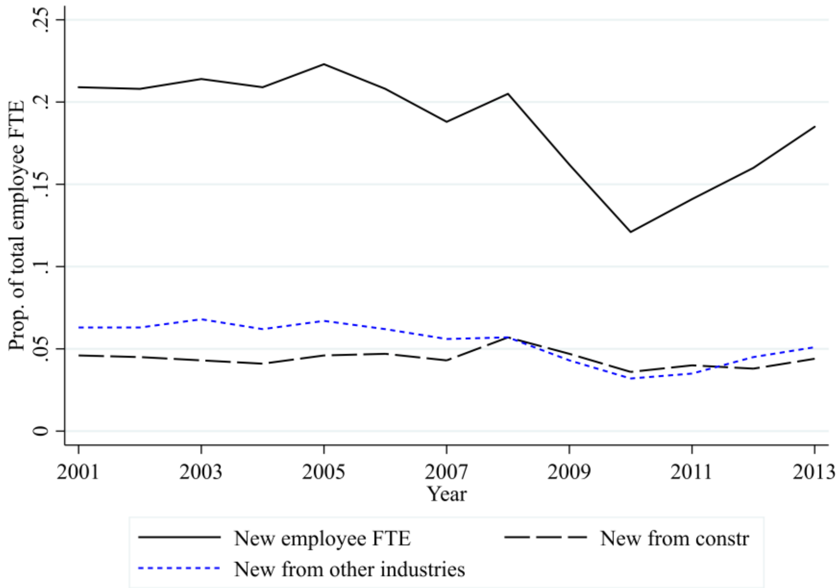
Appendix Table 4: Knowledge flows and productivity, different measure of knowledge flows

Dependent variable:	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**	**Log gross output**
New FTE from productive constr firms/firm size	**0.238*****	**0.047***	**0.237*****	**0.069**	**0.058**	**0.159***	**0.251*****	**0.032**
	(0.030)	**(0.026)**	**(0.065)**	**(0.053)**	**(0.100)**	**(0.083)**	**(0.031)**	**(0.028)**
New FTE from unproductive constr firms/firm size	-0.057***	0.003	0.010	0.044	-0.061	0.094	-0.091***	-0.022
	(0.020)	(0.016)	(0.039)	(0.033)	(0.094)	(0.076)	(0.025)	(0.018)
New FTE from productive non-constr firms/firm size	0.040	-0.020	0.083	-0.025	-0.003	-0.057	0.027	-0.017
	(0.032)	(0.027)	(0.063)	(0.041)	(0.114)	(0.120)	(0.038)	(0.034)
New FTE from unproductive non-constr firms/ firm size	0.059**	0.059***	0.105**	0.067*	-0.136	-0.062	0.047*	0.060**
	(0.023)	(0.021)	(0.041)	(0.037)	(0.114)	(0.114)	(0.028)	(0.026)
New FTE from misc sources/ firm size	0.020**	0.012*	0.025*	-0.013	-0.066	-0.019	0.021*	0.026***
	(0.009)	(0.007)	(0.013)	(0.012)	(0.076)	(0.083)	(0.011)	(0.008)
New WP labour from productive constr firms/firm size	**0.171*****	**0.028*****	**0.146*****	**0.001**	**0.267*****	**0.061**	**0.179*****	**0.040*****
	(0.010)	**(0.009)**	**(0.017)**	**(0.016)**	**(0.053)**	**(0.051)**	**(0.012)**	**(0.011)**
New WP labour from unproductive constr firms/ firm size	-0.032***	-0.009	-0.028*	-0.009	0.189*	0.019	-0.039***	-0.012
	(0.010)	(0.011)	(0.016)	(0.020)	(0.109)	(0.070)	(0.013)	(0.012)
New WP labour from productive non-constr firms/ firm size	0.184***	0.041**	0.151***	0.056	0.219**	0.091**	0.194***	0.033
	(0.022)	(0.019)	(0.035)	(0.046)	(0.099)	(0.045)	(0.027)	(0.021)
New WP labour from unproductive non-constr firms/ firm size	-0.044	-0.024	-0.125	0.031	0.207	0.087*	-0.037	-0.052
	(0.041)	(0.029)	(0.109)	(0.047)	(0.149)	(0.045)	(0.038)	(0.038)
New WP labour from misc sources/ firm size	-0.000	-0.039***	0.006	-0.027***	0.087***	-0.008	-0.005	-0.045***
	(0.004)	(0.004)	(0.007)	(0.006)	(0.024)	(0.024)	(0.004)	(0.004)
Ever seen entering (2001 onwards)	0.056***		0.076***		0.127***		0.045***	
	(0.004)		(0.007)		(0.023)		(0.005)	
Observations	281,379	281,379	90,690	90,690	8,577	8,577	182,112	182,112
R-squared	0.886	0.670	0.886	0.682	0.942	0.724	0.877	0.660
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Industries included	All constr with lvl 2 FE	All constr	Building constr	Building constr	Heavy & civil	Heavy & civil	Constr services	Constr services

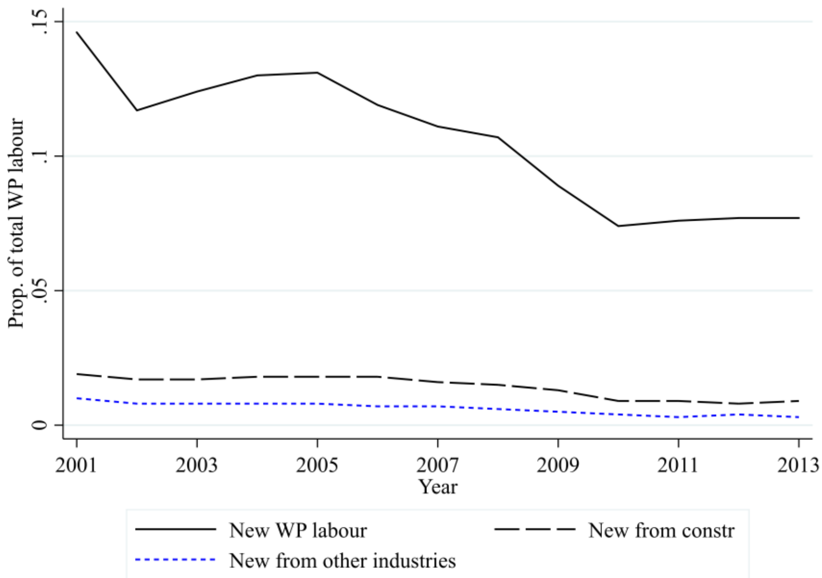
Notes: All regressions also control for log of capital, log of labour, log of intermediate materials, year and region fixed effects, and include dummy variables for being an entrant, an exiter, having production data from AES survey, and for being in Canterbury in the post-earthquake period. A productive firm is one whose Cobb-Douglas MFP residual is larger than zero, meaning the firm is more productive than the industry average that year. See further notes in Table 5.

Appendix figures

Appendix Figure 1: Proportion of employee FTE in construction that is new



Appendix Figure 2: Proportion of working proprietor labour in construction that is new



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