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Productivity and the allocation of skills

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Abstract

We use linked employer-employee data from 2004–2012, combined with individual qualifications data from 1994–2012, to study how graduates with different skills fare in the labour market in the six years after studying. We find that graduates experience improvements in earnings, and that they systematically move between jobs, industries and locations in a pattern that is consistent with their securing better job matches, particularly for high level STEM graduates.

We then estimate joint production function and wage equations to see how the skill composition of a firm's employees correlates with productivity, and compare this with how the skill composition correlates with its wage bill. Our results suggest that degree graduates make a growing positive contribution to production in the six years after graduation, with associated wage growth. There is variation in relative productivity and wages across groups of graduates that differ by field of study and level of qualification.

JEL codes

D29, J24

Keywords

Firm productivity, linked employer-employee data, skill matching, STEM

Summary haiku

Graduates learn skills

Earnings and production grow

Does the job matter?

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Tables and Figures

1 Introduction

A reliable supply of high-quality technical skills is a key ingredient for a productive and innovative economy that can compete in global markets. This paper focuses on the early career employment dynamics of young science, technology, engineering and maths (STEM) graduates to gauge the importance of finding the 'right' jobs that can make use of STEM skills. We examine changes in the sort of firms and locations where graduates work in the first 6 years after graduation. We also estimate the relative contribution that young graduates make to firm productivity, and how this compares with the wages that they receive – distinguishing level of qualification, time since graduation, and field of study.

The availability of rich educational and labour market data from Statistics New Zealand's Integrated Data Infrastructure (IDI) has enabled recent research in New Zealand on skills and economic performance to switch its focus from the firm level to the individual level. The current paper follows this strand of research by examining the matching of skilled individuals to firms, and the contribution of skill allocation to firms' productivity performance versus its wage bill. In particular, the paper seeks to estimate productivity and wage premiums for high-skilled labour, measured by the proportion of a firm's employees with high-level STEM (Science, Technology, Engineering and Mathematics) qualifications. A comparison of productivity and wage differentials for high-skilled recent graduates sheds light on whether these employees are compensated in line with their contribution to productivity.

We initially focus on the way that people with different skills (as captured by qualifications) are allocated among employing firms. Looking at the four cohorts of students graduating from 2003–2006 who do little or no further study, we document the quality of the firms in which graduates find work, and how graduates upgrade in the six years after graduation. The second part of analysis is at the firm level, and compares wage premiums for skilled labour with productivity premiums, to detect whether wage growth reflects changes in productivity early in workers' careers.

As such, this paper complements existing research on productivity and skills that relies on a proxy for skill that does not exploit the richness of the educational data in the IDI.[1] It also lays the foundation for possible subsequent studies of the productivity and wage impacts of skill diffusion and knowledge transfer; a specific example could be tracing the impacts of workers who move between different sorts of firms to see if productivity advantages of firms are transmitted to other firms when workers move; or the analysis of skill dynamics over business cycles, to reveal how retention of skilled workers is reflected in measured productivity, or in the ability of firms to recover from downturns and adapt to change.

[1] See, for example, Maré et al. (2015).

Section 2 briefly reviews related international and New Zealand studies that examine the impacts of STEM skills. The New Zealand studies rely on qualification-based measures of skills, or use linked employer-employee data to examine worker skills and firm performance. The data and criteria for sample selection are described in Section 3. Section 4 describes how people with different skills (as captured by qualifications) are allocated among employing firms. Section 5 presents estimation results on the productivity and wage impacts of skilled labour. Section 6 summarises and concludes.

2 Background

In an influential and extensive report, the US National Academy of Sciences Committee on Science, Engineering and Public Policy highlighted the important role that STEM skills play in economic success. Their report "emphasizes the need for world-class science and engineering—not simply as an end in itself but as the principal means of creating new jobs for our citizenry as a whole as it seeks to prosper in the global marketplace of the 21st century." (COSEPUP 2007, p. 40) While there is wide acceptance of this general view, there are nonetheless ongoing debates in many countries about whether the quantity or mix of STEM skills is right, and on whether non-STEM skills deliver similar benefits. Debates often conflate the question of the importance of increased supply of STEM skills in the longer-term with questions about short term balancing of the supply and demand of skills.

Carnevale et al. (2011) summarise ongoing debates about whether there is an oversupply or undersupply of STEM skills. They point out that measuring the supply of or demand for STEM skills using data on qualifications or occupations is imperfect because there is only a loose correspondence between fields of study or occupations and the prevalence of the sort of skills, knowledge, abilities, and interests that are commonly associated with STEM fields of study. In a similar vein, OECD (2014, p. 236) highlights the "contribution to innovation of training that goes beyond the traditional focus on [STEM] disciplines", and a recent Canadian report notes that:

> STEM skills have been advanced as central to innovation and productivity growth, which are in turn necessary for improving standards of living. While the general reasons behind this logic are clear, the Panel had difficulty finding direct and robust evidence that STEM skills are unique in this regard. (Council of Canadian Academies and Expert Panel on STEM Skills for the Future 2015)

Empirical studies of educational wage premiums by field of study find marked differences that are evident both within STEM fields and across STEM and non-STEM fields. Non-STEM fields such as economics, management and law command higher wage premiums than some STEM subjects (Walker and Zhu 2011), and returns depend also on the occupation in which graduates are working (Greenwood, Harrison, and Vignoles 2011). Siepel et al. (2016) argue that STEM and non-STEM skills complement each other. They examine the impact of STEM graduates on firm performance, and find that firms that employ a mix of Arts and STEM graduates perform better than firms with a less diverse mix.

Employing STEM graduates may generate spillover benefits that extend beyond the graduates themselves or the firms in which they work. Estimates for the US and Canada suggest a strong impact of foreign STEM graduates on economic growth (Peri, Shih, and Sparber 2015; Peri and Shih 2015).

2.1 Relevant New Zealand studies

New Zealand studies of STEM qualifications have generally focused on outcomes for graduates. A growing body of recent work in New Zealand has used the IDI to document graduate outcomes. They show that higher-level graduates do better in the labour market, and that there are important differences in outcomes by field of study. Scott (2009), Mahoney et al. (2013) and Park et al. (2014) together show that earnings and employment rates increase with the level of qualification and that, by broad field of study, people graduating with degrees in engineering, health and IT had the highest median earnings in subsequent years after study. Park (2014) shows a large proportion of young graduates go overseas after studying; nearly a third of bachelors graduates were overseas (for at least nine months) in their seventh year after study.

Crichton and Dixon (2011) use propensity score matching to investigate the labour market returns to gaining an undergraduate certificate or diploma for adults aged 25 to 64. Comparing people who are similar in terms of demographics and prior earnings- and employment-trajectories, the results suggest further education does little to boost adults' earnings. The authors suggest this is because few people in their data are truly increasing their qualifications and skills; 60 percent were already qualified at an equivalent or higher level. Tumen et al. (2015) use a similar matching method to look at the impact of tertiary study on the outcomes of people who leave high school without completing NCEA level 2. Their results suggest a small positive impact on employment rates, though only for those who complete their qualifications, and no impact on earnings.

Maré and Liang (2006) use 1996 and 2001 census data to analyse labour market outcomes for young tertiary graduates and the distribution of graduates across different sorts of jobs. They find that STEM graduates are not especially highly concentrated in particular industries or occupations, although they do not provide separate estimates for different levels of qualification. They report that median incomes for young science graduates are low relative to graduates generally, and that engineering graduates have relatively high median incomes. Computer and information science graduates have low median incomes overall, but reasonably high median incomes for high-level qualifications (Bachelor's degree and above).

Our study extends the existing literature by providing new information on which firms graduates match with. Previous work in New Zealand has captured skills through worker fixed effects, and shown a positive correlation between worker and firm fixed effects; better workers tend to locate at better firms (Maré and Hyslop 2007; Maré, Sanderson, and Fabling 2014). By focusing on the narrow subset of recent graduates, we directly measure skills using qualification levels and fields, and can shed light on the dynamic process of how graduates match with different firms, and to what extent graduates 'upgrade' their jobs in their first six years of employment.

3 Data

This study uses rich administrative data from Statistics New Zealand's Integrated Data Infrastructure (IDI).[2] The IDI is an integrated data environment with longitudinal microdata about individuals, households and firms. The data are obtained from several sources, including sample surveys, tax records and other administrative sources.

Since the purposes of this paper are to document the way that people with different skills are allocated among employing firms and to estimate productivity-wage differentials, we need data on qualifications, personal demographics, personal employment and firm characteristics. Below we briefly discuss the sources for each data category. Appendix Table 1 contains the definitions of key variables.

3.1.1 Qualifications

Information on qualifications are from the Ministry of Education (MOE)'s data on enrolments (from 1994), courses (from 2000) and qualification completion (from 1994) at the tertiary level. From these data we use qualification award category codes (QACC) to classify each qualification as one of the following: level 1-4 certificates; diplomas; graduate diplomas/certificates; bachelor's degrees; honours degrees and postgraduate diplomas/certificates; master's degrees; and doctorates. For much of our analysis we further group qualifications into one of two broad levels: a qualification is 'high' if it is at the bachelor's degree level or above (excluding graduate certificates and diplomas), and is 'low' otherwise.

We use the New Zealand Standard Classification of Education (NZSCED) to infer the main field of study for a qualification, with the concordance between field of study and NZSCED codes shown in Appendix Table 2.[3] A STEM qualification is then one in science (including agricultural science) and mathematics, IT, or engineering.[4]

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[2] 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.

[3] Where possible we use the NZSCED field of study variable created by MOE researchers, which uses field information on each course taken to get an accurate picture (Scott 2009). When this variable is unavailable, as is the case from 1994–2002 due to the lack of course data, we use the university-provided NZSCED codes.

[4] There is no universally accepted definition of STEM. We include Agricultural Science in STEM as it is often implied in the New Zealand policy context (see, for example, Cumming 2014). Smart (2015) discusses STEM fields of study in New Zealand but does not provide an explicit definition. Australian Bureau of Statistics also includes Agricultural Science in its STEM definition (Australian Bureau of Statistics 2014). Our definition is narrower than that of the US NSF, which includes social sciences (National Science Board 2016)

Graduation year is based on the course completion date from completion data.

3.1.2 Personal demographics

We link MOE data to the IDI's core demographic table, which draws on multiple data sources to form Statistics NZ's most accurate picture of each person's characteristics. This allows us to know the gender and age of graduates. All of our graduate outcomes analysis is limited to those who were aged 30 or younger at graduation. This enables us to focus on the matching outcomes of graduates with little prior exposure to the labour market.

3.1.3 Personal employment

Data on employment are taken from the Employer Monthly Schedule (EMS). Each month all employers file an EMS record with Inland Revenue, which lists all employees at that firm in the month, the amount of income they received, and the amount of tax that was deducted at source. This is the key data source that links workers to firms. From this we can calculate gross earnings; employment duration and employment location for each paid job; and the number of paid jobs a person has. We use these data to explore the employment outcomes of STEM and non-STEM graduates.

3.1.4 Firm characteristics

Firm-level data are taken from the Longitudinal Business Database (LBD), a component of the IDI which in turn draws on a number of different data sources. The LBD contains tax- and survey-based financial data, merchandise and services trade data, a variety of sample surveys on business practices and outcomes, and government programme participation lists (Fabling and Sanderson 2016), providing information on firms' demographic characteristics, business activity and performance.

We gather data on firms' total wages paid and full-time equivalent (FTE) labour, with both coming from Fabling and Maré (2015a). Plant-level data in the LBD show the location of firms (which may operate out of several plants/locations). We also derive the employment density of the Area Unit a plant operates in. Data on firm wage fixed effects come from the work of Maré and Hyslop (2006) and Maré et al. (2015). These represent the constant premium a firm pays all its employees, and present an attractive alternative to only looking at the wages a firm pays; the latter may be high just because a firm employs many highly-skilled, highly-paid workers.[5]

Firm-level data in the LBD are usually organised annually by the tax year (April to March), though when looking at graduate outcomes we aggregate monthly earnings data to calendar year measures. Productivity data for Section 5 are obtained from the productivity dataset documented in Fabling and Maré (2015b). The Fabling and Maré (2015b) dataset uses LBD data

[5] We do not look at worker wage fixed effects, which represent the portable earnings premium of each individual, because we are most interested in the dynamic matching of graduates with firms. The estimated worker fixed effects will be correlated with worker qualifications, but for the current paper we use qualifications directly.

from the Annual Enterprise Survey (AES) and Inland Revenue (IR) to create firm-level measures of real gross output (revenue-based measure); capital services; and intermediate consumption.

Throughout the paper we classify industry using the production function industries of the productivity dataset, which are mostly grouped at the second level of Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006 codes.[6] This groups firms into 50 industries for the graduate outcomes analysis in Section 4, and into 39 industries for the firm level analysis requiring productivity data in Section 5.

3.2 Sample selection

3.2.1 Graduation cohorts: 2003–2006

In constructing our main sample for looking at graduate outcomes, we start with all tertiary qualifications completed during 2003–2006[7], by people 30 years or younger in the year of completion. Domestic and international students are both included in the sample. We consider only qualifications requiring at least 0.5 EFTS and having at least one 'formal course with at least 1 week duration'.[8] This restriction focuses attention on graduates who devote a significant amount of time to study and on formal qualifications that are likely to be associated with significant skill development. When a student completes multiple qualifications in the same year, we consider only the qualification with the highest level.[9]

For each graduate in our sample, we explore how they fare in the labour market after graduation, which requires a unique graduation year. For people completing multiple qualifications over 2003–2006, we restrict attention to the highest qualification gained during the period. When there are multiple qualifications of the same level, the most recent graduation is used.[10]

Table 1 summarises the number of graduates that are included in the resulting dataset, disaggregated by level of qualification and whether the qualification gained is in a STEM field. We group young graduates into one of the four following groups: high STEM graduates, who have a bachelor degree or above in a STEM field; high non-STEM graduates, who have a bachelor degree or above in a non-STEM field; low STEM graduates, who have a sub-bachelor qualification in a STEM field; and low non-STEM graduates, who have a sub-bachelor qualification in a non-STEM field. We test whether high qualification levels tend to reflect higher

[6] Fabling and Maré (2015b) describes where the industry classification deviates from the two-digit level. This deviation is driven by sample size and the availability of industry-specific deflators.
[7] Even though MOE completion data are available from 1994, we include only data from 2003 onwards, as pre-2003 years had a poor matching rate into the IDI, and the field of study measure that we use to identify STEM fields is calculated only from 2003. The final cohort year is 2006 to ensure we have sufficient data in the six years after graduation.
[8] For these qualifications, the IDI variable moe_enr_qual_type_code takes on the value 'D'.
[9] In case of multiple qualifications of the same level, we pick the 'primary qualification' based on total EFTS loading, data completeness, provider code (lower numeric code tends to be associated with longer established institutions), and subject code. This method is a convenient shortcut to avoid double counting people in the analysis.
[10] If a person gained multiple qualifications of the same level in the same year, we choose the qualification with the lowest NZSCED code, with the lowest codes corresponding to STEM fields.

skills, and whether studying a STEM field tends to result in skills that are valuable to employers.[11] We also supplement this by narrowing in on the individual categories within STEM for bachelor-and-above graduates, and include health graduates as a comparison group.[12]

Table 1: Selected Populations, 2003–2006 graduates

	High		Low		Total
	STEM	non-STEM	STEM	non-STEM	
1) Broad cohorts	19,737	66,804	17,733	83,121	187,395
2) Excluding further study (unless always employed)	16,212	59,541	14,043	61,776	151,575
3) Always employed	4,539	14,220	4,731	14,217	37,704

Note: Based on data from Statistics New Zealand's Integrated Data Infrastructure (IDI). See section 3.2.1 for definitions and discussion. Population counts have been randomly rounded.

There are 187,395 young graduates included in our dataset, 46% of whom graduated with a Bachelor's degree or above, and 20% of whom graduated with a qualification in a STEM field of study. Around one in five of the graduates undertake significant study (more than 1.5 EFTS) in the six years following their graduation. [13] In order to focus attention on post-graduation employment, we distinguish graduates who continue to study. The sample shown in the second row of Table 1 excludes such graduates, unless they are also employed for at least half time in each of the six years following their graduation, as identified from FTE employment.

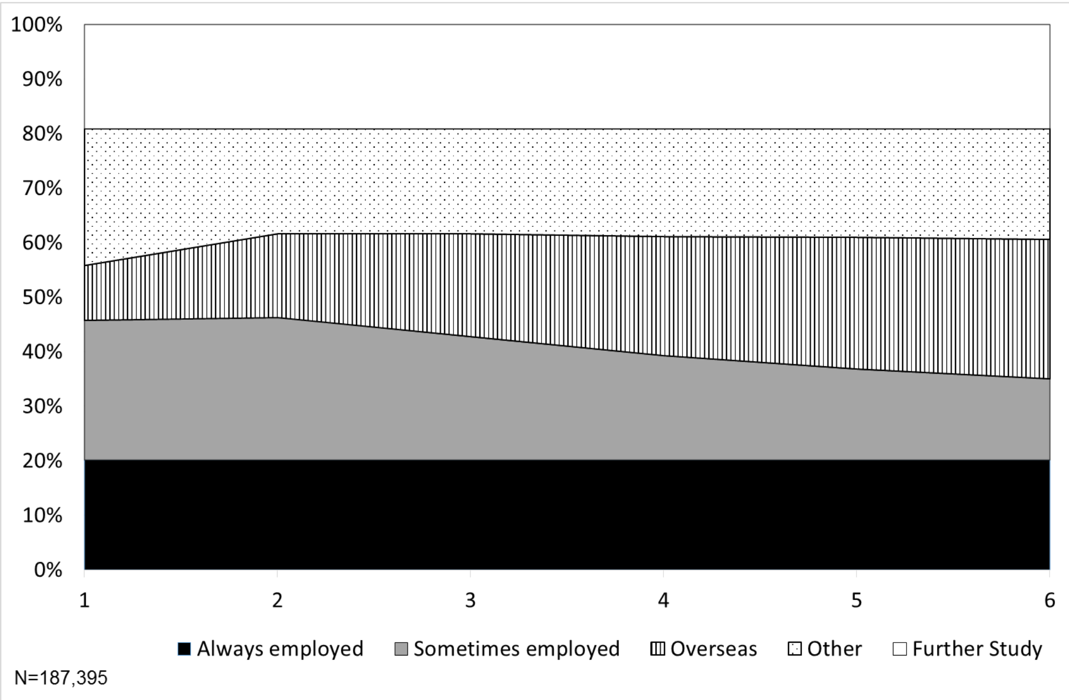
For much of our analysis of graduate outcomes, we use an 'employed' subset of the 2003–2006 cohorts, selecting only those graduates who work at least 0.5 FTE years in each of the six years following graduation, which we refer to as 'always employed'.[14] As shown in the third row of Table 1, there are 37,704 graduates in this sample. STEM graduates account for a higher proportion of the employed subset (25%) than of the broad cohort set (20%), due to their higher employment rate over six years.

These restrictions considerably decrease the number of students in the analysis, but help ensure we focus on graduates entering the labour market for full-time work. Figure 1 summarises outcomes for the 'broad cohorts' population of 187,395 graduates in the six years

[11] Previous NZ work discussed in the literature section shows that graduates in the non-STEM fields of health, accounting and law have high employment rates and median earnings. It also seems clear that medical practitioners, accountants, lawyers and others have skills that are very valuable in the labour market. Nonetheless we focus on STEM vs. non-STEM for the reasons discussed in the introduction; STEM students are likely to tend to have high skills, and regardless there is strong policy interest (throughout the world) in encouraging STEM graduate numbers.
[12] We group science and mathematics together, as there are very few mathematics graduates. The motivation for comparing with health graduates comes from previous NZ literature, which shows that health graduates have among the highest earnings and employment rates. We cannot compare health graduates to STEM graduates in the productivity analysis because the productivity dataset excludes the health sector, where many health graduates are employed.
[13] This corresponds to an average of more than 0.25 EFTS per year, reflecting only partial engagement in the labour market. The graduation date is the one chosen by the criteria of the previous paragraphs. So we do not, for example, exclude someone who completed a bachelor's degree in 2003, and then an honours degree and master's degree over the next two years. Rather, the future EFTS are counted in the six years following the master's degree.
[14] Graduates who move overseas will not be in this dataset, as we have no employment information for them.

after graduation. The 'always employed' subset of 37,704 graduates accounts for 20% of the pooled cohorts. In the first year after graduation, 46% of graduates were employed more than half time (including the 20% who are employed more than half time in all 6 years). Ten percent were overseas for at least 9 months of the year, and the remaining 25% were classified as 'other', meaning that they did not fall into any other category. The 'other' group accounts for a smaller proportion of the cohorts in the second to sixth year after graduation. There is an associated rise in the proportion overseas, from 10% in the first year to 15% in the second year, and continuing to increase through until the sixth year after graduation, when 25% of the cohorts are overseas. The proportion of the graduation cohorts that are observed with more than half-time employment in the sixth year after graduation drops to 35%, largely reflecting the exclusion of graduates who have left New Zealand. It is a limitation of our analysis that we cannot observe those who train overseas, the specific employment outcomes of those who travel overseas, or those who are self-employed or who work in the informal sector after graduating.

Figure 1: Composition of 2003–2006 young graduate cohorts



Notes: Proportions in Figure 1 are pooled over four cohorts, from 2003 to 2006. The 'always employed' and 'further study' shares are constant over time by construction, calculated as the proportion of graduates who work at least 0.5 FTE in all six years following graduation, and the proportion who go on to study more than 1.5 EFTS over the following six years. Graduates are 'overseas' in a year if they are out of the country for at least 9 months; 'sometimes employed' in a year if they don't fit any of the first three categories and work at least 0.5 FTE in that year; and 'other' if they fit none of the other four categories in a year. A (randomly rounded) total of 187,395 graduates (each followed for six years) make up this figure, labelled as population (1) in Table 1.

The pattern of post-graduation destinations differs somewhat by level of qualification and, to a lesser extent, between STEM and non-STEM graduates. (The patterns are summarised in Appendix Figure 1). Graduates with a Bachelor's degree or above are most likely to leave New

Zealand, with around a third of graduates out of New Zealand for at least 9 months in the sixth year after graduation. This compares with fewer than 20% for sub-degree graduates. High non-STEM graduates are least likely to pursue significant further study. Only 11% of the graduation cohorts undertake more than 1.5 EFTS of study in the six years following graduation, compared with 18% for STEM degree graduates, and 21% and 26% respectively for sub-degree STEM and non-STEM graduates. STEM graduates are more likely than non-STEM graduates to work more than half time in each of the six years following graduation. The proportion is highest for sub-degree STEM graduates (27%).

3.2.2 Sample selection for firm-level analysis

When analysing the relative productivity and wages of graduates, in section 5, we maintain the classification of graduates by STEM field and by level of qualification, but no longer focus attention only on the 2003-2006 cohorts of graduates. For this analysis, we first select a subset of firms, and then classify employees within those firms according to their qualifications, where possible.

We restrict our analysis to firms with a sufficiently large number of employees to make qualification shares meaningful. Specifically, we exclude firms that are never observed with at least 10 full-time equivalent employment at some point between 2001 and 2012, and drop observations for years in which a firm's employment is lower than 5 FTE. We require data on firm production, and are therefore limited to firms included in the productivity dataset documented in Fabling and Maré (2015b), which includes data until the 2012 financial year. This dataset includes only firms in the measured sector, identified by Statistics New Zealand as "industries that mainly contain enterprises that . . . sell their products for economically significant prices that affect the quantity that consumers are willing to purchase" (Statistics New Zealand 2014). This restriction excludes government, education and health industries.

Firms' FTE employment is disaggregated by gender and by qualification group. As in the descriptive analysis above, qualifications are classified by field (STEM or non-STEM) and level (with qualifications at Bachelor's level or above classified as 'high'). In addition, we distinguish employees who are recent graduates from those who graduated less recently. We identify 'new' graduates as those who graduated fewer than 3 calendar years prior to the month in which they are observed as employees.[15] Our ability to identify earlier graduates is limited by the available data on qualification completions and field of study, which is of lower quality prior to 2003, as noted in footnotes 3 and 7. We capture earlier graduates who are observed as employees 3 to 6 years after their graduation, and consequently restrict our analysis of firm productivity to the

[15] Both graduation year and year of employment are classified by calendar year. 'New' graduates could thus have graduated 1 to 47 months prior to the month they are observed in employment. Employee qualifications are calculated for each month, and aggregated to match firms' financial years. During a financial year, an employee's qualification classification can change.

2009 to 2012 financial years, to ensure a consistent 6-year window over which to observe employees' qualifications.

Only around 10% of employees are observed completing a tertiary qualification in the 6 years prior to their employment. The productivity and wages of these employees is compared to the productivity and wages of all other employees combined. The combined 'base' category includes employees without a tertiary qualification, as well as tertiary-qualified graduates who graduated earlier, or who graduated outside New Zealand.

We use production and employee composition information on an average of 10,700 firms per year for the four years 2009 to 2012. These firms collectively employ an average of 620,000 FTE employees per year, accounting for around 80% of employment in firms included in the productivity dataset.[16] The number of firms is, however, only 5% of the total due to the exclusion of many small firms from our analysis. The firm-level dataset used for estimating relative wages and productivity of different graduate groups is discussed in further detail in section 5.

4 Graduate outcomes

4.1 Composition of graduate cohorts

Table 2 provides a more detailed summary of the composition of graduate cohorts. It disaggregates the 'broad cohort' and 'always employed' populations shown in Table 1 (rows 1 and 3) by year and by level of qualification.

[16] The production dataset accounts for about 75% of employment in covered industries, and about 70% of total employment. The lack of coverage is largely due to requiring production data, and the exclusion of non-for-profit firms and those not in the private sector.

Table 2: Graduates by level and field, 2003–2006 cohorts

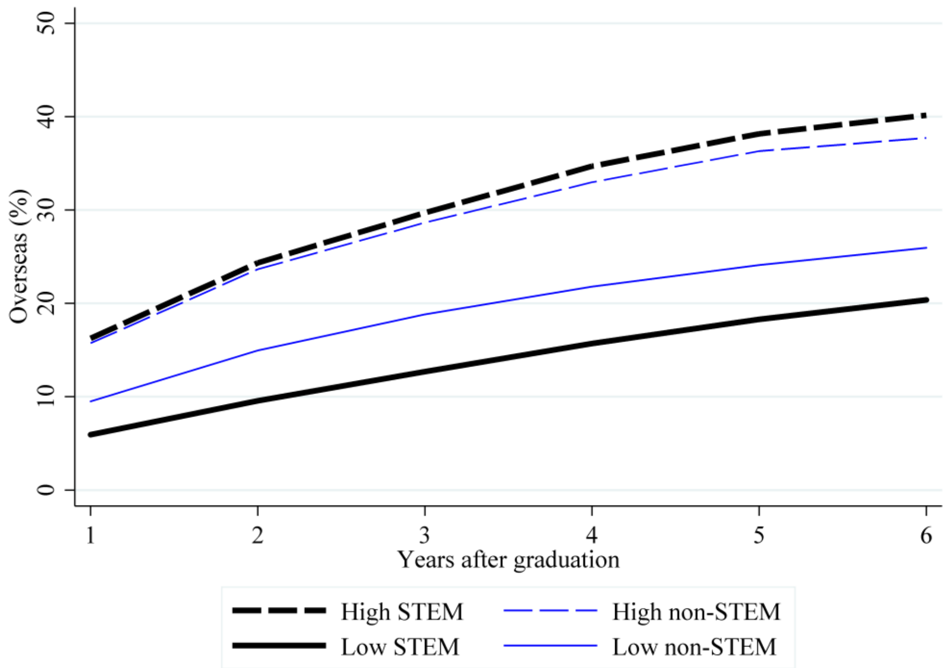
	Broad cohorts		Employed cohorts	
	STEM	Non-STEM	STEM	Non-STEM
2003				
Lvl 1-4 cert	2,541	13,200	768	2,157
Diploma	1,461	5,406	393	1,011
Grad dip/cert	138	1,641	33	489
Bachelor's	2,403	10,488	594	2,361
Hons & pg	990	1,671	204	354
Master's	474	903	108	150
Doctorate	93	39	24	9
2004				
Lvl 1-4 cert	2,715	12,837	783	2,052
Diploma	1,488	6,165	366	1,134
Grad dip/cert	150	1,206	30	324
Bachelor's	2,715	11,955	651	2,649
Hons & pg	1,188	1,869	279	426
Master's	609	1,050	135	183
Doctorate	108	45	27	12
2005				
Lvl 1-4 cert	2,772	13,029	747	2,133
Diploma	1,578	6,180	384	1,095
Grad dip/cert	150	939	30	264
Bachelor's	3,018	13,959	711	2,937
Hons & pg	1,317	2,229	291	483
Master's	648	1,341	150	255
Doctorate	126	39	27	12
2006				
Lvl 1-4 cert	3,186	14,469	852	2,151
Diploma	1,362	7,200	312	1,200
Grad dip/cert	192	852	36	207
Bachelor's	3,750	16,932	813	3,516
Hons & pg	1,593	2,829	360	621
Master's	597	1,401	138	246
Doctorate	111	48	27	12
All years				
Lvl 1-4 cert	11,214	53,535	3,150	8,493
Diploma	5,889	24,951	1,455	4,440
Grad dip/cert	630	4,638	129	1,284
Bachelor's	11,886	53,334	2,769	11,463
Hons & pg	5,088	8,598	1,134	1,884
Master's	2,328	4,695	531	834
Doctorate	438	171	105	45
Total	37,473	149,922	9,273	28,443

Notes: Table includes data on all young (30 years or younger) graduates who: complete a qualification during 2003–2006 which requires at least 0.5 EFTS and has at least one formal course longer than a week; Data are based on populations (1) and (3) as summarised in Table 1. See section 3.2.1 for more details. Population counts have been randomly rounded.

The number of non-STEM graduates exceeds the number of STEM graduates at all qualification levels except for doctorates, though STEM students tend to be more highly represented in the employed cohorts. STEM students are also more highly represented at higher qualification levels, for both broad and employed cohorts. When pooled across all years, STEM students account for 23% of graduates with a Bachelor's degree or above, but 37% of graduates with a post-graduate qualification. The difference is even more pronounced for 'always employed' graduates, where STEM graduates account for 24% of those with a Bachelor’s or above, and 39% of those with a post-graduate qualification.

4.2 Overseas movement

Figure 2: Proportion of young graduates who are overseas



Notes: Proportions in Figure 2 are calculated over a broad sample of cohorts that excludes those undertaking further study (population 2 in Table 1, with the additional exclusion of graduates who appear to be overseas for 12 months but who are employed for at least 0.1 FTE). We consider a graduate to be ‘out of the country’ in a calendar year if they are overseas for at least nine months.

Figure 2 pools together the four cohorts from 2003–2006 and shows the percentage of young graduates who are overseas in each of the six years following graduation, where we consider someone overseas if they are out of the country for at least 9 months in a calendar year.[17] Many graduates go overseas; the *lowest* percentage in the 6th year after graduation is over 20 percent, for low-STEM graduates, while the highest is a striking 40 percent for high-STEM graduates. The proportions are very similar for high STEM and high non-STEM graduates in all years, though low STEM graduates have a lower proportion overseas than low non-STEM graduates in all years. These numbers tell us little about how differently-skilled graduates fare in the labour market, as we do not know what graduates do overseas, but they make it clear that New Zealand’s skilled graduates are very mobile. The general pattern of rising average

[17] This follows the criterion used by Park (2014).

emigration rates in the six years after graduation, and higher emigration rates for graduates with higher-level qualifications is similar to findings for other New Zealand studies of graduate mobility (Smart 2006; Papadopolous 2012; Smyth and Spackman 2012; Park 2014). Our estimates are somewhat higher, possibly due to our inclusion of international students, and our focus on younger graduates.[18] Both of these groups have relatively high probabilities of going overseas.

Appendix Figure 2 shows movement patterns among high-level STEM graduates. There is some variation by field of study, though the proportion of graduates who are overseas six years after graduation is similar for engineering, maths/science, and IT graduates at around 40%. Health graduates, by comparison, are more likely to be in New Zealand, with only 30% out of the country six years after graduation. Maths/science graduates are more likely than other fields to be out of New Zealand within two years of graduating, with 30% overseas compared with around 20% for other fields.

4.3 Employment matching

The linked employer-employee data that we use allows us to examine the early-career transitions that graduates make between jobs, employers, and locations. This provides insights into how important it is for STEM graduates to find a job that is a good match with their skills. For this analysis, we focus on graduates from 2003-2006 who are observed working at least half time in each of the six years following graduation. This analytical population comprises 37,704 graduates and is shown as population 3 in Table 1. Figure 3 provides a graphical summary of changes experienced by graduates in their first 6 years after graduation. We discuss differences over time and between graduate groups in job changes, whom they work for and where they work.

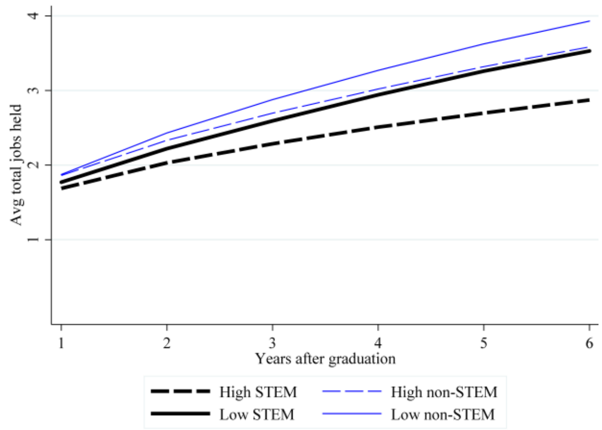
4.3.1 Number of job changes

We hypothesise that STEM graduates in general have more specialised skills than graduates in many other non-STEM fields. It is therefore plausible that the success of STEM graduates depends to a greater extent on finding a good match – with an employer who requires the specialist skills. It is, however, an empirical question whether STEM graduates change jobs more often than other graduates in their quest to find the 'right' job, or if non-STEM graduates complement their more general skills with experience in a larger number of different jobs.

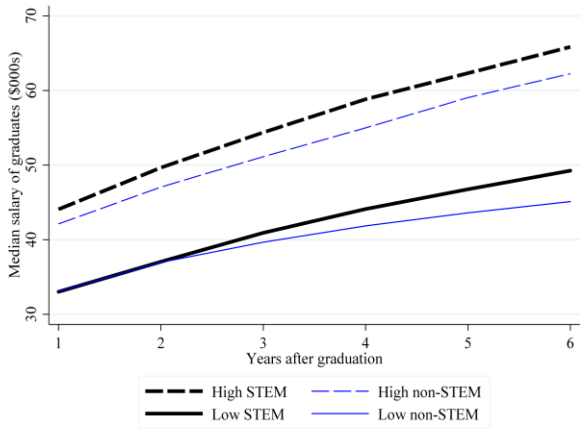
[18] The studies also differ in the definition and measure of being overseas, and in sample selection. Smart (2006) restricts attention to holders of student loans, and uses a tax-based definition of residence. Other authors restrict attention to domestic students, and consider broader age ranges.

Figure 3: Changes in graduate outcomes in 6 years after graduation

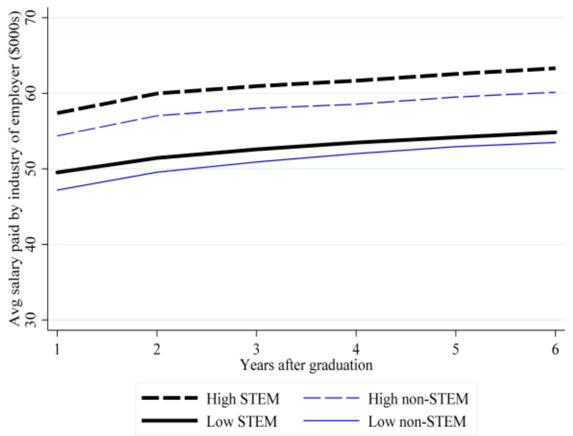
(a) Average number of jobs



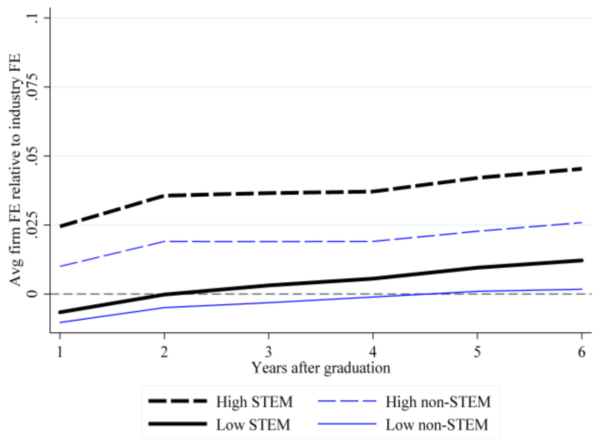
(b) Median earnings



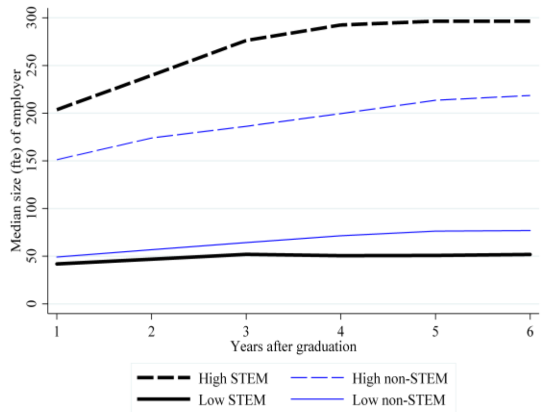
(c) Industry average earnings



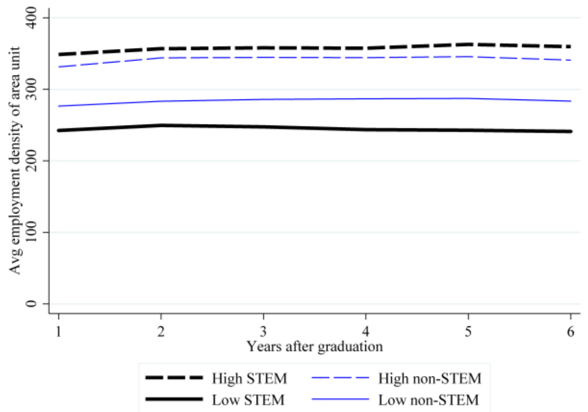
(d) High-paying firms



(e) Firm size



(f) Local employment density



Notes: Proportions in the figure are calculated over the 'always employed' subset of graduates (population 3 of Table 1). In the case of multiple jobs in a year, we weight observations by the FTE worked in each job. Industry average salary is an FTE-weighted average of employer wages paid per FTE. The industry average fixed effect is an FTE-weighted average of each firm's fixed effect. Earnings are in real 2009 dollars, deflated using the labour cost index.

The first panel of Figure 3 shows that high STEM graduates make a relatively low number of job changes early in their careers, on average starting 2.9 new jobs in their first 6 years after graduation. In comparison, non-STEM graduates with less than a Bachelor's degree start 3.9 different jobs.

4.3.2 Earnings

Although a high proportion of early career wage growth is associated with job changes (Topel and Ward 1992; Neal 1999), high-STEM graduates experience relatively rapid earnings growth despite their relatively low number of job changes. We measure earnings as the median level of FTE-adjusted annual earnings (2009 dollars) for each group. Of the four graduate subgroups shown in the second panel of Figure 3, high-STEM graduates not only have the highest median earnings rate in the first year after graduation ($45,000), they also have the strongest growth in median earnings over their first six years post-graduation (49%). Among graduates with less than a Bachelor's degree, STEM and non-STEM graduates have similar starting rates ($33,000) but earnings grow more strongly for STEM graduates (49%) than for non-STEM graduates (36%).

Panels *c*, *d* and *e* of Figure 3 show whether early career wage growth is associated with changes in industry, or with movements to higher-paying or larger employers.

4.3.3 Industries

To capture the contribution of inter-industry mobility, we index industries by the average FTE-adjusted annual earnings rate of its employees, and then show whether graduates move from lower-paying industries to higher-paying industries. This is indeed the pattern for all graduate groups, though with the magnitude of change (10–11%) being similar for all groups except non-STEM sub-degree graduates (13%).

4.3.4 Employers

To identify whether graduates move to higher-paying firms, we use an index of employers' pay structures, relative to the average for their industry. This index is estimated as a time-invariant firm-specific wage premium, estimated from a two-way worker-firm fixed effect model, as in Maré et al (2015).[19] The index is normalised to have an FTE-weighted mean of zero across all employing firms in each industry, so that the value of the index is approximately equal to the percentage wage premium paid by the firm. Graduates with a Bachelor's degree or above are employed by relatively high-paying firms in their first year after graduation. Employers of first-year high-STEM graduates pay an average premium of 2.5%. High non-STEM graduates start

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[19] The resulting index captures whether a firm pays relatively high or low wages, controlling for the composition of its employees. A firm that pays high average wages because it disproportionately employs highly skilled or qualified workers will only be identified as a high-payer if it pays those workers a higher than average rate of pay. Separating worker and firm effects is made possible by the availability of linked employer employee data, and the ability to observe pay changes when workers move between firms (Abowd and Kramarz 1999).

their careers with employers that pay, on average, a 1% premium. In contrast, graduates who qualify with less than a Bachelor's degree on average start their careers with employers who pay lower than their industry average, though only around 1% below average.

All graduate groups move to higher-paying firms in their first 6 years after graduation, with about half of the gains made between the first and second year of employment. The gains over 6 years are highest for STEM graduates. High-STEM graduates on average move to firms that pay 2.1% more than their first-year employers and low-STEM graduates to firms that pay 1.9% more. For non-STEM graduates, the 'upgrading' of employers is less pronounced, with changes of 1.6% and 1.2% respectively for those with higher-level and lower-level qualifications.

The movement to higher paying firms may reflect the importance of job matching for more specialised graduates with high-level qualifications, and for STEM graduates in particular. High-paying firms are likely to be those that are producing more differentiated products, or those that are able to capture the gains from specialisation (see, for example, Fabling & Maré (2016), who show that firms that export, invest in R&D, or innovate have higher average firm fixed effects). Further evidence that is consistent with this interpretation is that high-level STEM graduates generally work for larger employers, and increasingly move to larger employers over their first six years after graduation. The gains to specialisation are likely to be greater in larger firms, and we would therefore expect firm size to be a further important indicator of the quality of job matches for graduates with specialised skills.

Panel *e* of Figure 3 shows the relative size of firms that employ different graduate groups, where firm size is measured as the median number of FTE employees. Graduates with a Bachelor's degree or higher are disproportionately employed in large firms. In their first year after graduation, high-STEM graduates are in firms with median size of 204 FTEs and other high-level graduates are in firms of 151 FTEs. In their first 6 years of post-graduation employment, each of these groups moves to firms that are, on average, around 45% larger than their first-year employers (to firms of size 296 and 219 respectively). Sub-degree graduates start off in smaller employers, with median size of between 40 and 50. They too move to larger employers, though the increases for low-STEM graduates (from 42 to 52) are less pronounced than those for low non-STEM graduates (from 49 to 77).

4.3.5 Location

Graduates with specialised skills are more likely to find a job that matches their skills well in a dense urban labour market (Wright, Ellis, and Townley 2016). We would therefore expect STEM graduates to move to denser areas in the years following graduation. We investigate this pattern in two ways. First, we index the locations in which graduates work by local employment density (number of jobs per km^2)[20] and see whether graduates move towards areas where density is higher. Second, we summarise how likely different types of graduates are to work in Auckland in the years after they graduate, controlling for where they gained their qualification.

There is limited change in the employment density of areas in which graduates work in the years following graduation, as shown in panel (f) of Figure 3. Graduates with Bachelor's degrees or above work in denser labour markets throughout their first six post-graduation years but the average density is relatively stable, varying between 330 and 360. High STEM graduates work in slightly more dense areas than do other graduates with Bachelor's degree or higher. Sub-degree graduates work in less dense areas, with sub-degree STEM graduates on average working in the least dense areas. Variation over time is small, though sub-degree STEM graduates, on average work in slightly less dense areas six years after graduation than in their first post-graduation year.

Table 3: Mobility of 'always employed' graduates in and out of Auckland

	Place of study	Number of graduates	% studied in Akld	Probability of work location 6 years after graduation: in Akld	Probability of work location 6 years after graduation: outside Akld
High-STEM	Auckland	1,887	42%	83%	17%
	Not Auckland	2,643		20%	80%
		4,530		46%	54%
High non-STEM	Auckland	5,259	37%	82%	18%
	Not Auckland	8,913		20%	80%
		14,172		43%	57%
Low STEM	Auckland	1,371	29%	80%	20%
	Not Auckland	3,354		11%	89%
		4,725		30%	70%
Low non-STEM	Auckland	4,335	31%	81%	19%
	Not Auckland	9,864		18%	82%
		14,199		37%	63%
Total	Auckland	12,852	34%	82%	18%
	Not Auckland	24,774		18%	82%
		37,626		39%	61%

Note: Data are based on the 'always employed population (3 as summarised in Table 1). See section 3.2.1 for more details. Population counts have been randomly rounded. This table excludes 60 graduates whose study or job location could not be accurately identified.

Table 3 summarises the geographic mobility of graduates in the 6 years after graduation. It contrasts the probability of graduates working in Auckland or elsewhere, conditional on whether they studied in Auckland. Overall, 82% of Auckland graduates were working in Auckland and 82% of non-Auckland graduates were working outside Auckland. Because fewer

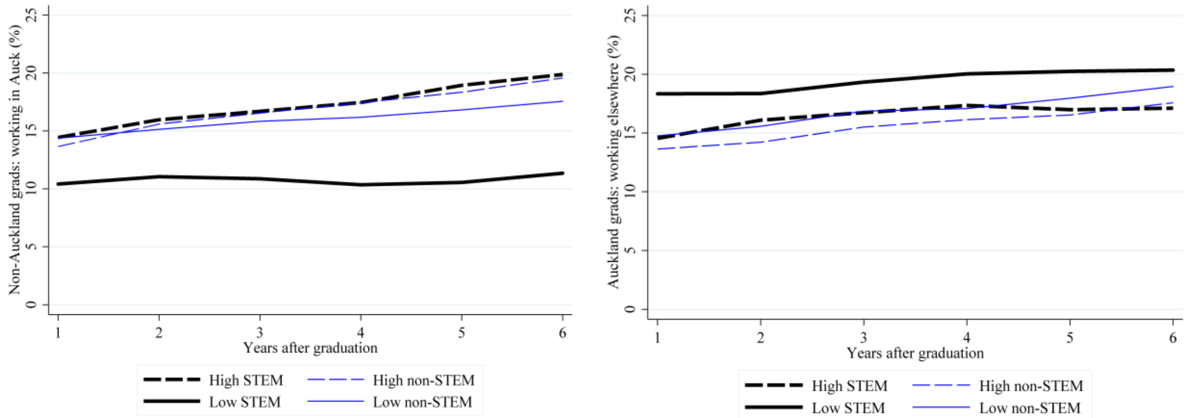
[20] Employment density is measured for each area unit (AU) (approximately a suburb in urban areas). For each AU, we calculate a spatially weighted annual average that includes all AUs within 20km of the workplace area unit (based on AU centroids).

than half of graduates had studied in Auckland, the graduate flow into Auckland exceeded the outflow, and 39% of graduates were working in Auckland after 6 years, which was higher than the 34% who studied there. The strength of reallocation was similar for all graduate groups except sub-degree STEM graduates. For this group, only 11% of non-Auckland graduates were working in Auckland after 6 years, and 20% of Auckland graduates had left Auckland. The benefits of working in a large dense city appears to be less pronounced for low STEM graduates, and the need for such qualified graduates is relatively strong in areas outside Auckland.

The time profile of movements into and out of Auckland is shown in Figure 4. Net mobility (both in and out of Auckland) increases over time for non-STEM graduates, with sub-degree graduates decreasingly likely to be working in Auckland. High STEM graduates are increasingly likely to be working in Auckland, both because non-Auckland graduates are increasingly likely to move to Auckland, and because Auckland graduates on average are increasingly likely to return to Auckland for work. Finally, the relatively low probability of low STEM graduates living in Auckland is evident in Figure 4 and is fairly stable over the 6 years.

Figure 4: Movement to and from Auckland

Non-Auckland graduates: working in Auckland *Auckland graduates: working elsewhere*



Notes: Proportions in this figure are calculated only for the 'always employed' subset (population 3 of Table 1). In the case of multiple jobs in a year, we weight observations by the FTE worked in each job.

4.3.6 Variation by field of study

Employment matching patterns for high STEM graduates do vary somewhat by field of study. Appendix Figure 3 documents the variation for graduates differentiated by broad field of study, for engineering, science and maths, and IT. It also shows, for comparison, the patterns for graduates in health with a Bachelor's degree or higher.

The main difference from the overall patterns shown in Figure 3 is that the increased sorting into high-paying firms is most strongly evident for Engineering and IT graduates. IT graduates also experience the strongest change in firm size, increasingly moving to larger firms, although they are employed in smaller firms than are other graduates. Median firm size for health graduates is large relative to other fields – unsurprisingly given that hospitals are generally large employers.

Engineers who graduated outside Auckland are most likely to move to Auckland in the six years following graduation. IT graduates who studied in Auckland are the Auckland graduates least likely to be working outside Auckland in the years following graduation, though Auckland engineering graduates are also more likely to be retained in Auckland than maths and science or health graduates (See Appendix Figure 4).

5 Productivity and wages of recent graduates

In this section, the description of graduate outcomes is complemented by an analysis of the impact of graduates on firm performance. This analysis is not restricted to the cohorts of graduates whose outcomes were summarised in the previous section. Instead, we analyse a sample of firms that operated in the 2009 to 2012 financial years, and distinguish labour input provided by recent (graduated within 3 calendar years) and less recent (graduated 3 to 6 years earlier) graduates. The selection of the sample is described above in section 3.2.2. Table 4 and Table 5 provide a more detailed summary of the data. We use information on 10,700 firms per year, each with FTE employment of at least 5.[21] Around 64% of these firms employ fewer than 25 FTE employees, although most employment (73%) is in firms with 50 or more FTE employees.

Table 4: Production data: by year and FTE employees

	2009	2010	2011	2012	Total
		Number of firm-year observations			
5 to 24.9 FTE employees	7,107	7,071	6,846	6,384	27,405
25 to 49.9 FTE employees	2,007	1,881	1,890	1,869	7,647
50 FTE employees or larger	2,061	1,968	1,899	1,944	7,872
Total	11,175	10,920	10,635	10,197	42,921
		Total FTE employee count (000)			
5 to 24.9 FTE employees	104.2	101.4	99.2	94.4	399.2
25 to 49.9 FTE employees	69.7	65.6	66.1	65.3	266.6
50 FTE employees or larger	471.0	449.0	439.9	446.0	1,806.0
Total	645.0	616.0	605.1	605.7	2,471.9

Note: Counts of firms and sums of FTE employment have been randomly rounded. See section 3.2.2 for more details.

[21] Working proprietors are not included for this restriction. They are included in measures of labour input but the skill and gender composition of firms is based on employees only.

Table 5: Production data: Sex and qualification composition

	Qualifications			Firm Size			
	Level	STEM	Within 3 years	FTE in [5,25)	FTE in [25,50)	FTE 50 plus	Total
Men				63.9%	65.6%	63.2%	64.1%
Women				36.1%	34.4%	36.8%	35.9%
Graduates	High	Yes	Yes	0.3%	0.4%	0.5%	0.4%
Graduates	High	Yes	No	0.4%	0.6%	0.6%	0.5%
Graduates	Low	Yes	Yes	0.7%	0.7%	0.7%	0.7%
Graduates	Low	Yes	No	0.8%	0.8%	0.8%	0.8%
Graduates	High	No	Yes	1.2%	1.2%	1.3%	1.2%
Graduates	High	No	No	1.3%	1.3%	1.4%	1.3%
Graduates	Low	No	Yes	2.2%	2.0%	2.0%	2.1%
Graduates	Low	No	No	2.5%	2.3%	2.4%	2.4%
Graduates	Missing	Missing	Missing	90.7%	90.7%	90.4%	90.6%
Mean FTE				14.6	34.9	229.4	57.6

Note: Mean FTE based on rounded sums of FTE and rounded counts of firms. Qualification composition relates to graduates employed in firms that appear in the production data, and who graduated fewer than 6 years prior to their employment. See section 3.2.2 for more details.

The bottom row of Table 5 shows the mean firm size of 57.6 FTE employees. On average, men account for 64.1% of the FTE labour input in these firms. Information on the qualification composition of labour input is restricted to employees for whom we can identify a completion in the 6 years prior to a month in which they are employed. This information is not available for 90.6% of FTE labour input. Employees identified as high-STEM graduates account for 0.9% of total labour input, with a further 1.5% from sub-degree STEM graduates. Non-STEM graduates account for a larger proportion of labour input, contributing 7% overall, with 2.5% from high-level graduates, and 4.6% from sub-degree graduates. For each group, the contribution of recent (within 3 years) graduates is slightly lower than the contribution of employees who graduated 3 to 6 years earlier.

The relative contributions of different graduate groups to firm productivity and to wage costs is identified from variation between firms and over time in the share of labour input provided by the different groups. The contributions are measured relative to the contribution of the 90.6% of labour input provided by employees not included in any of the graduate groups. Measures of relative contributions will therefore be similar in magnitude to differences from mean contributions.

5.1 Modelling framework

We compare the relative contributions of different skill groups to production with their relative wage levels, following the approach of Hellerstein et al. (1999; 2007). A firm's gross output is modelled as a second-order (translog) approximation to an arbitrary production function (Christensen, Jorgenson, and Lau 1973) that combines capital inputs (X_K) intermediate inputs (X_M) and effective labour inputs ($X_{\tilde{L}}$):

$$lnY = \alpha + \sum_{j=K,\tilde{L},M} lnX_j \left(\beta_j + \sum_{m=K,\tilde{L},M} \frac{\beta_{jm}}{2} lnX_m \right) \tag{1}$$

Effective labour input is modelled as a function of the quantity of labour supplied by workers, differentiated by sex and qualifications. The marginal product of each class is measured relative to that of a common base group, with relative productivity $\phi_c \left(\phi_c = \frac{Y_{L^c}}{Y_{L^1}} \right)$. This measure of relative productivity is compared with the class' relative wage $\theta_c \left(\theta_c = \frac{w_c}{w_1} \right)$, identified by the relationship of the firm's total wage bill (W) with the share of labour input provided by each class.

Wage premiums by sex (s) and qualification (q) are modelled as multiplicative. Relative to a male worker with a base level of qualification (s=1; q=1), a worker's wage $w_{sq} = w_{11} * (\theta_s)(\theta_q)$. With this assumption, the wage bill (W) paid by a firm to its employees can be expressed as a function of the employment and relative wages of different workers, as follows:

$$W = \sum_c w_c L^c = w_{11} L \left(\frac{L^M}{L} + \theta_F \frac{L^F}{L} \right) \left(\frac{L^1}{L} + \sum_{q=2}^{Q} \theta_q \frac{L^q}{L} \right) \tag{2}$$

The contributions of different workers to production is modelled analogously. Men and women are assumed to supply different amounts of perfectly substitutable labour input, as are workers with different qualifications. Effective labour input is modelled as:

$$X_{\tilde{L}} = \mathrm{L} \left(\frac{L^M}{L} + \phi_F \frac{L^F}{L} \right) \left(\frac{L^1}{L} + \sum_{q=2}^{Q} \phi_q \frac{L^q}{L} \right) + \phi_{WP} WP \tag{3}$$

The factor ϕ_F represents the contribution of a woman to production, relative to that of a man, which is normalised to equal one. Similarly, ϕ_q capture the relative contributions of workers with different qualifications, measured relative to a base-category. Effective labour input of working proprietors is captured by the final term of the equation, with ϕ_{WP} reflecting their relative contribution.

We assume that the benchmark wage of the omitted group of employees (w_{11}) is proportional to that group's marginal product ($\mathrm{w}_{11} = \mathrm{rY}_{L^{11}}$). Combining equation 1 and 3 and differentiating with respect to L^{11} yields the following expressions for w_{11}:

$$w_{11} = rY_{L^{11}} = \underbrace{\frac{rY}{\mathrm{X}_{\tilde{L}}}\frac{\partial lnY}{\partial lnX_{\tilde{L}}}}_{\frac{\partial Y}{\partial X_{\tilde{L}}}} * \underbrace{\frac{\mathrm{X}_{\tilde{L}}}{L} * \left(\left(\frac{L^M}{L} + \phi_F\frac{L^F}{L}\right)^{-1} + \left(\frac{L^1}{L} + \sum_{q=2}^{Q}\phi_q\frac{L^q}{L}\right)^{-1} - 1\right)}_{\frac{\partial X_{\tilde{L}}}{\partial L_{11}}}$$

$$= \frac{\mathrm{r}Y}{L}\left(\beta_{\tilde{L}} + \sum_{m=K,\tilde{L},M}\beta_{\tilde{L},m}lnX_m\right) * \underbrace{\left(\left(\frac{L^M}{L} + \phi_F\frac{L^F}{L}\right)^{-1} + \left(\frac{L^1}{L} + \sum_{q=2}^{Q}\phi_q\frac{L^q}{L}\right)^{-1} - 1\right)} \tag{4}$$

Substituting the expression for w_{11} into equation 2 gives an expression for the firm's wage bill:

$$W = \mathrm{r}Y\left(\beta_{\tilde{L}} + \sum_{m=K,\tilde{L},M}\beta_{\tilde{L},m}lnX_m\right) * \left(\left(\frac{L^M}{L} + \phi_F\frac{L^F}{L}\right)^{-1} + \left(\frac{L^1}{L} + \sum_{q=2}^{Q}\phi_q\frac{L^q}{L}\right)^{-1} - 1\right)$$
$$* \left(\frac{L_M}{L} + \theta_F\frac{L^F}{L}\right)\left(\frac{L^1}{L} + \sum_{q=2}^{Q}\theta_q\frac{L^q}{L}\right) \tag{5}$$

We wish to test whether the ratio of paid wages, relative to the base category, $\left(\theta_F = \frac{w_F}{w_M};\ \theta_q = \frac{w_q}{w_1}\right)$ equals the ratio of marginal products for different qualification groups and, separately, for different sexes, relative to the base categories. The ratio of marginal products for qualification groups is evaluated holding the mix of men and women constant. Similarly, the sex-ratio of marginal products is evaluated holding the qualification mix constant. Relative marginal products are then equal to the values of ϕ_F and ϕ_q. Testing whether $\phi_c = \theta_c$ tests whether the ratio of paid wages equals the ratio of marginal products for each class of workers.

5.1.1 Estimation

The estimating equations are based on equations 1 and 5, with effective labour ($\mathrm{X}_{\tilde{L}}$) defined as in equation 3.

$$ln(Y_{it}) = \left[\alpha^Y + \sum_{j=K,\tilde{L},M} ln(X_{jit})\left(\beta_j + \sum_{m=K,\tilde{L},M}\frac{\beta_{jm}}{2}ln(X_{mit})\right) + Z_{it}^Y\psi^Y\right] + e_{it}^Y$$

$$ln(W_{it}) = \left[\alpha^Y + \sum_{j=K,\tilde{L},M} ln(X_{jit})\left(\beta_j + \sum_{m=K,\tilde{L},M}\frac{\beta_{jm}}{2}ln(X_{mit})\right) + Z_{it}^Y\psi^Y\right] + ln\left(\beta_{\tilde{L}} + \sum_{m=K,\tilde{L},M}\beta_{\tilde{L},m}ln(X_{mit})\right)$$
$$+ln\left(\frac{1}{\left(\frac{L^M}{L} + \phi_F\frac{L^F}{L}\right)} + \frac{1}{\left(\frac{L^1}{L} + \sum_{q=2}^{Q}\phi_q\frac{L^q}{L}\right)} - 1\right) + ln\left(\left(\frac{L_M}{L} + \theta_F\frac{L^F}{L}\right)\left(\frac{L^1}{L} + \sum_{q=2}^{Q}\theta_q\frac{L^q}{L}\right)\right) \tag{6}$$
$$+\alpha^W + Z_{it}^W\psi^W + e_{it}^W$$

In the output equation, the intercept is allowed to vary by industry and year (Z_{it}^Y) with the production function parameters are constrained to be common across industries. There is also an unobserved component of output (e_{it}^Y) which captures un-transmitted random variation. The intercept of the wage equation reflects the ratio of base-category wages to base-category marginal product (r in equation 5). The wage bill equation incorporates variation in this intercept by industry and year (Z_{it}^{W}) and an error term (e_{it}^{W}) to capture unobserved variation. Such variation may arise due to rent-sharing or to variation in technologies.

The output and wage bill equations are estimated as a system of non-linear equations. All of the parameters in the output equation $\left(\left\{\beta_j\right\}; \left\{\beta_{jm}\right\}; \{\psi^Y\}; \left\{\phi_c\right\}\right)$ are identified by the output equation alone and are also included in the wage bill equation. The wage bill equation identifies the relative wage parameters ($\{\theta_c\}$) and the coefficients on wage-related firm characteristics ($\{\psi^W\}$). Standard errors are estimated allowing for clustering by enterprise.

5.2 Estimated productivity and wage relativities

Estimates of relative productivity premiums (ϕ) and relative wage levels for different groups (θ) are shown in Table 6, based on estimation of the system of equations shown as equation 6. The final two columns include estimates of the implied difference between these relative contributions ($\theta - \phi$), and the difference as a proportion of relative productivity ($(\theta - \phi)/\phi$). In the context of gender differences, Hellerstein et al. (2007) refer to proportional difference as discrimination – being the proportion of productivity that is not reflected in wages. A negative ratio implies that a group contributes relatively more to productivity than to wage bills. The upper panel of Table 6 presents estimates based on pooled information on all firms. The lower panel restricts the sample to larger firms (25 or more FTE employees) to show whether the relative contribution of more specialised high-STEM graduates is greater in larger firms. As shown in Figure 3, STEM graduates move into progressively larger firms after graduating. If this reflects the ability of larger firms to make more productive use of specialised skills, we would expect to see stronger contributions in larger firms. The estimated premiums, and the difference between relative wage and productivity contributions, are also shown graphically in Figure 5.

The implied gender gap estimates are similar to the findings of Hellerstein et al. (2007), and similar to recent estimates for New Zealand using similar data (Sin, Stillman, and Fabling 2016), though Sin et al. also document substantial variation across industry. Based on FTE labour input, a woman is estimated to contribute 82.7 percent as much as a man to firm production ($\phi_F = 0.827$). This estimate is likely to be biased downward due to limitations of the FTE measure used. Part-time work is more prevalent among women and part time workers are more likely to be misclassified as full-time, leading to an understatement of true productivity per FTE. The bias would, however, affect the estimated contribution to wages in the same way. The relative wage of women is, however, estimated to be lower than the contribution to production, being only 78.6 percent of the men's wage ($\theta_F = 0.786$). The proportional difference (-5%) suggests that women are underpaid given their average contribution to production.

Table 6: Production data: Estimates of relative productivity and wages

	Relative Productivity (ϕ)	Relative wage (θ)	Difference ($\theta - \phi$)	%diff $\left(\frac{\theta - \phi}{\phi}\right)$
	All firms			
Women	0.827***	0.786***	-0.040***	-5%
	(0.023)	(0.011)	(0.000)	
Recent STEM degrees	0.724*	0.890***	0.166	23%
	(0.380)	(0.151)	(0.106)	
Older STEM degrees	1.774***	2.238***	0.464***	26%
	(0.323)	(0.161)	(0.082)	
Recent STEM sub-degree	0.031	0.400***	0.369***	1190%
	(0.164)	(0.093)	(0.019)	
Older STEM sub-degree	0.976***	0.857***	-0.119***	-12%
	(0.174)	(0.087)	(0.028)	
Recent non-STEM degrees	1.645***	1.092***	-0.553***	-34%
	(0.225)	(0.087)	(0.043)	
Older non-STEM degrees	2.808***	1.647***	-1.161***	-41%
	(0.237)	(0.098)	(0.059)	
Recent non-STEM sub-degree	0.294***	0.448***	0.154***	52%
	(0.104)	(0.050)	(0.010)	
Older non-STEM sub-degree	0.548***	0.668***	0.120***	22%
	(0.114)	(0.052)	(0.011)	
Other workers (Base)	1	1	0	
Number of observations	42,921			
	Firms with 25 or more FTE employees			
Women	0.852***	0.761***	-0.091***	-11%
	(0.043)	(0.020)	(0.001)	
Recent STEM degrees	0.665	0.712**	0.047	7%
	(0.729)	(0.300)	(0.404)	
Older STEM degrees	3.261***	2.706***	-0.554	-17%
	(0.856)	(0.332)	(0.504)	
Recent STEM sub-degree	-0.554	-0.219	0.336**	-60%
	(0.459)	(0.218)	(0.165)	
Older STEM sub-degree	1.151**	1.000***	-0.151	-13%
	(0.492)	(0.235)	(0.195)	
Recent non-STEM degrees	1.263**	0.853***	-0.410	-32%
	(0.551)	(0.191)	(0.257)	
Older non-STEM degrees	5.106***	2.614***	-2.492***	-49%
	(0.607)	(0.234)	(0.347)	
Recent non-STEM sub-degree	0.066	0.239*	0.173**	262%
	(0.292)	(0.142)	(0.069)	
Older non-STEM sub-degree	0.072	0.624***	0.552***	767%
	(0.330)	(0.157)	(0.077)	
Other workers (Base)	1	1	0	
Number of observations	15,519			

Note: Table contains regression estimates of equation 6. Regression also includes time and industry dummies in both the production and wage bill equations. Standard errors are adjusted for clustering by enterprise. Observation counts have been randomly rounded

Gender variation in relative wages and productivity is small relative to the variation across different graduate groups. The relative wage of recent graduates with a Bachelor's degree or above is estimated to be similar to the wage of the base category – 89% for STEM graduates, and 109% for non-STEM graduates. For recent sub-degree graduates, relative wages are 40% to 45% of base category wages. As noted in the context of gender gaps, the magnitude of these relative wage estimates (θ_c) is likely to be biased by mismeasurement of FTE. Differences in the composition of different groups by age, occupation, or location will also lead to an estimate of the relative wage that may not accurately reflect the true relative wage. For each group, however, the relative wage estimate and relative productivity estimate will be affected by bias in the same way, so are expected to be comparable in magnitude. A gap between the relative wage and relative productivity could reflect a range of labour market factors, including discrimination, as argued by Hellerstein et al (2007). It could also reflect various forms of incentive contract, under which workers are paid below their productivity early in their careers to induce effort or discourage turnover, leading to an upward sloping age earnings profiles (Lazear 1981; Hellerstein and Neumark 1995).

In our application, the estimated wage-productivity gaps may also be influenced by cyclical variation. Outcomes within the first 3 years after graduation are observed in the years 2004 to 2009 whereas 3-6 year outcomes are observed in 2007-2012. Wages tend to vary less over the cycle than productivity does, so productivity contributions differ from wage contributions for cyclical reasons, though the direction of bias is not obvious.

The relative productivity of recent high STEM graduates (72%) is lower than the estimated relative wage, though the difference (0.166 or 23% of productivity) is not statistically different from zero. In contrast, the productive contribution of recent high non-STEM graduates (165% of the base group) is significantly higher than their relative wage, with an implied difference of -34% of productivity.

The estimates for older (3-6 years post-graduation) graduates with a Bachelor's degree or above show a marked rise in both relative wages and relative productivity contributions compared with more recent graduates. For high STEM graduates, relative wages more than double, and rise well above those of the base category (224%), accompanied by a slightly smaller increase in relative productivity (177% of base category). Together these estimates imply that the wages of older high STEM graduates is 26% higher than their productivity contribution. In contrast, the relative wages of high non-STEM graduates grow by around 50% - less slowly than their relative productivity, magnifying the degree to which their relative productivity (281% of base) exceeds their relative wage (165% of base). Three to 6 years after graduation, wages for this group are 41% lower than their productivity contribution.

The relative wage and productivity contributions of sub-degree graduates are consistently lower than the contributions of degree graduates. The productivity contribution of recent sub-degree STEM graduates is estimated to be close to zero (3% of the base category contribution) and their relative wages are 40% of base category wages. The implied relative difference is very large (1190%) due to division by the small relative productivity.[22] Three to 6 years after graduation, sub-degree STEM graduates contribute about the same as the base category to both productivity (98%) and wages (86%). This implies a wage 'deficit' amounting to 12% of their productivity contribution.

Recent sub-degree graduates in STEM fields earn similar wages to comparable STEM degree graduates, but experience slower wage growth within 3-6 years of graduation. Non-STEM sub-degree wages rise from 45% to 67% of base category wages, and remain above their productivity contribution, which rises from 29% to 55% of the base category's contribution. The margin of wages over the productivity contribution remains positive, but narrows from 52% to 22%.

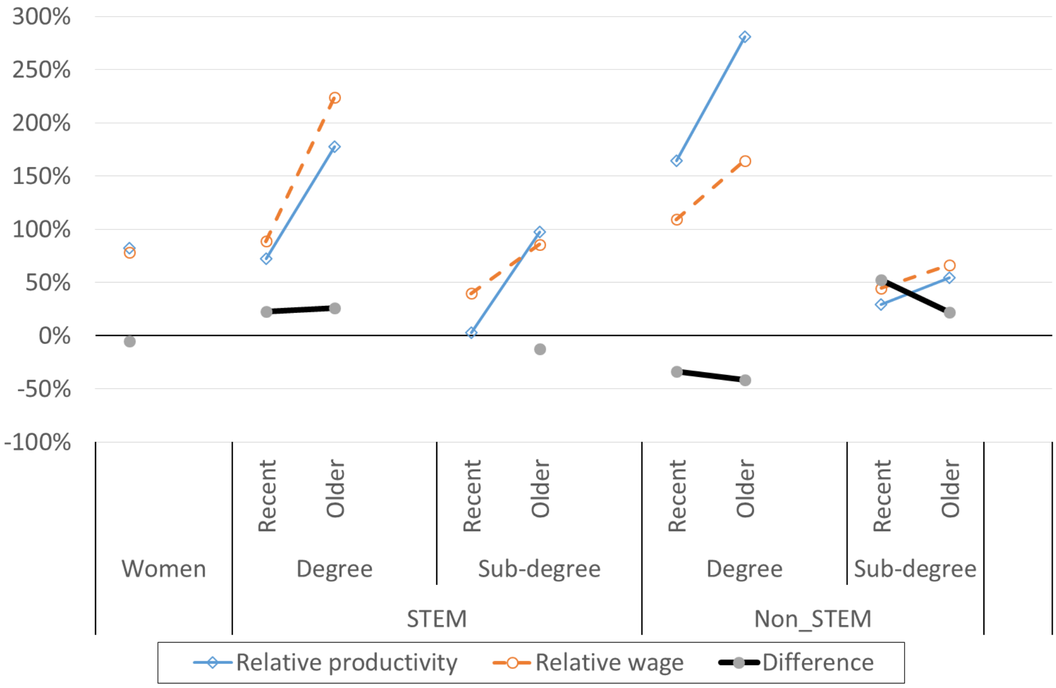
The lower panels of Table 6 and Figure 5 present analogous estimates for a subset of larger firms – those with FTE employment of at least 25. The general pattern of wage and productivity effects is similar to that seen across all firms. For degree graduates, initial wages are similar for STEM (71% of base category) and non-STEM (85% of base category) graduates, as are relative wages after 3 to 6 years (270% and 260% respectively). For high STEM graduates, the wage increase is approximately matched by productivity growth. For high non-STEM graduates, relative productivity growth outstrips wage growth, magnifying the wage penalty from -32% of productivity to -49% of productivity.

Sub-degree graduates in larger firms are estimated to contribute close to zero to productivity initially. For sub-degree STEM graduates 3-6 years after graduation, both wages and productivity have risen to about the same as that of the base category, with a relatively small (-13%) wage deficit. The estimated relative productivity of low non-STEM graduates remains close to zero even 3-6 years after graduation, although wages increase to around 62% of the base category. Estimates of the proportional difference between wage and productivity contributions is unstable when the estimated relative productivity contribution is close to zero (or negative, as in the case of recent sub-degree STEM graduates).

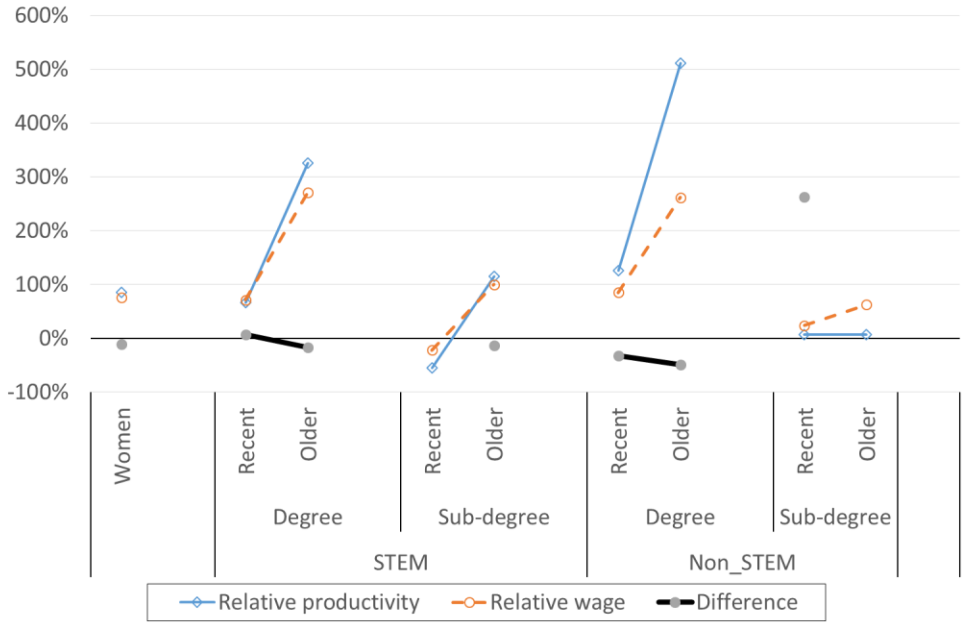
[22] This is not shown in Figure 5 due to the contrast in scale with other numbers.

Figure 5: Relative wage and productivity estimates

(a) All firms



(b)Firms with 25 or more FTE employees



Notes: This figure is a graphical display of coefficients that are shown in Table 6. The 'difference' shown in the figures corresponds to the final column of Table 6, and for presentational reasons is not plotted where the value exceeds 500 or the point estimate for relative productivity is negative.

6 Summary and discussion

There are two main sets of findings from this study. The first documents graduates' reallocation across jobs, firms, and locations in the first six years after graduation. The second estimates the productivity contribution of graduates and compares it to their estimated relative wage, initially and 3 to 6 years after graduation. In each case, separate patterns are shown for STEM and non-STEM graduates, and for graduates with different levels of qualification.

Patterns of reallocation are documented for a subset of young graduate cohorts from 2003-2006 who are observed working at least half time in each of the 6 years after graduation. This subset accounts for around 20% of the graduate cohorts. It excludes graduates who study for 1.5 EFTS within 6 years of graduation unless they're also consistently employed (19%), graduates who leave New Zealand (10% initially, rising to 26% by the end of six years), and graduates who are less consistently employed.

The early-career experience of employed graduates is one of rising earnings, and movement into higher paying firms and industries and larger firms. The reallocation is particularly concentrated in the first year or two after graduation. STEM graduates with a Bachelor's degree or above change jobs less than other graduate groups, but are more strongly sorted into high paying industries, high paying firms within industries, and into larger firms. The pattern of dynamics is more similar for degree graduates in STEM and other fields than it is for STEM graduates with different levels of qualifications.

Although we expect the rewards to technical skills to be greater in dense labour markets that support better matching and specialisation, there is not a strong reallocation of graduates to denser areas. We do, however, find that more graduates are employed in Auckland 6 years after graduation than studied in Auckland. The net flow of graduates to Auckland is weakest for graduates with sub-degree STEM skills, who are also most likely to be employed in areas with relatively low employment density.

The second part of the paper estimates the relative productivity and wage contributions of recent graduate employees. Consistent with the description of graduate outcomes and reallocation, the productivity contributions of degree-qualified graduates rises markedly between the first 3 years after graduation and the subsequent 3 years. Wages more than double for STEM graduates, and rise by around 50% for non-STEM graduates. Wage increases are accompanied by increases in relative productivity, though the increases are not exactly matched. The relative wage paid to high STEM graduates is around 25% higher than their contribution to productivity. In contrast, high non-STEM graduates are estimated to make a higher relative contribution to productivity, and their relative wage is lower than their relative productivity by around 35 to 40%. The wage and productivity contributions of high STEM graduates are more closely aligned within larger firms, suggesting perhaps that wage levels are linked to what such graduates could earn in larger firms.

Sub-degree graduates are estimated to contribute very little to productivity in their first 3 years after graduation, particularly in larger firms but they, too make stronger positive contributions in the following 3 years, accompanied by a growth in relative wages.

The estimates of wage and productivity impacts suggest that the distinction between high level (Bachelor's and above) graduates and lower-qualification graduates is more pronounced than the distinction between STEM and non-STEM graduates. This dichotomy of fields, however, almost certainly conceals considerable variation within each group. It should also be noted that the estimates are identified from within-industry variation in firm performance and workforce composition, and will therefore not reflect possible economy-wide influences that the supply of skills may have on the growth of innovative and knowledge-intensive sectors of the economy.

Overall, our findings demonstrate the dynamic nature of labour market outcomes and contributions of tertiary graduates in the years following graduation, as graduates change jobs and make an increasing contribution to firm productivity.

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Appendix Tables

Appendix Table 1: Definitions of key variables

Variable	Definition
Qualifications	
Graduation year	Calendar year in which qualification was completed
Level of qualification	Level of qualification as captured by QACC codes, and categorised into broader levels using the concordance shown in Appendix Table 2
High-level qualification	1 if qualification is at the bachelor level or above (excluding graduate diplomas and certificates). Derived from the level of qualification
Field of qualification	12 broad categories, as shown in Appendix Table 2
STEM qualification	1 if qualification is in Science (including agricultural science), IT, Engineering or Mathematics. Derived from the field of qualification.
Study location	Location of the campus where most of the courses for the qualifications were enrolled; if location of campus cannot be determined, we use the primary location of the institution
Personal demographics	
Age	= Current calendar year – year of birth; exact month of birth is not taken into account
Gender	Male or female.
Personal employment	
Earnings by calendar year	Total earnings from all jobs in calendar year, deflated using the labour cost index (2009 base year)
Employment location	Location of plant which pays the worker
Firm characteristics	
Industry	Industry code based on production function industries classified in Fabling and Maré (2015a).
Firm size	Average monthly FTE labour in a year
Wage bill	Total wages paid to employees in a year, from the Fabling-Maré labour dataset
Plant location	Location of the plant
Firm fixed effect	Representation of the time-invariant premium a firm pays to all its employees. Derived from the work of Maré and Hyslop (2006) and Maré et al. (2015), and drawn from the Fabling-Maré labour dataset
Production function variables	Real gross output, capital services, intermediate consumption, and FTE for a firm in a tax year. From Fabling and Maré (2015a)

Notes: Qualifications data come from the tertiary MOE data in the IDI (specifically the tables moe_clean.completion, moe_clean.course and moe_clean.enrolment). Personal demographics come from the core demographics table in the IDI (data.personal_detail). Personal employment data come from the EMS (ir_clean.ird_ems), while firm characteristics come from the LBD and the datasets created by the referenced papers. All data in this paper come from the 5 December 2014 archive of the IDI/LBD.

Appendix Table 2: Definitions of qualification level and field

Level of qualification	QACC codes	High v Low classification
Level 1-4 cert	34–60	Low
Diploma	25–33	Low
Grad dip/cert	21	Low
Bachelor's degree	20	High
Honours & postgrad dip/cert	12–14	High
Master's degree	11	High
Doctorate	1 & 10	High

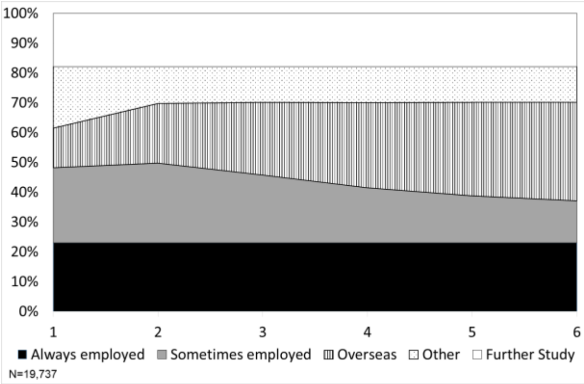
Field of study	NZSCED codes	STEM v non-STEM classification
Math & science	10101–19999	STEM
IT	20101–29999	STEM
Engineering	30101–39999	STEM
Architecture & building	40101–40399	Non-STEM
Agricultural science	50101–59999	STEM
Health	60101–69999	Non-STEM
Education	70101–79999	Non-STEM
Management & commerce	80101–89999	Non-STEM
Society & culture	90101–99999	Non-STEM
Creative arts	100101–109999	Non-STEM
Food, hospitality & personal services	110101–110399	Non-STEM
Mixed field programmes	120101–129999	Non-STEM

Notes: where available (from 2003) we use the NZSCED codes derived from MOE researchers, as detailed in Scott (2009). These derived codes use course information to draw the best conclusion about the true main field of study. Where not available, we use the NZSCED codes provided from tertiary institutions describing students' main fields of study.

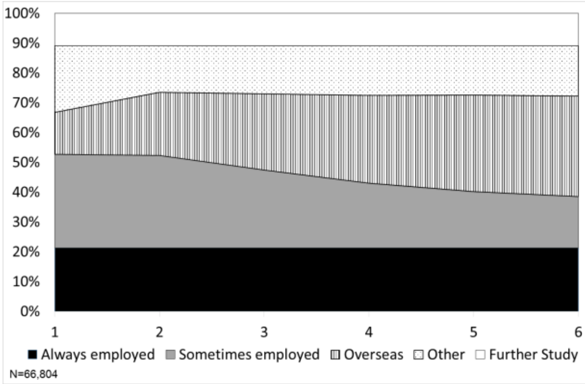
Appendix figures

Appendix Figure 1: Composition of 2003–2006 high-STEM cohorts

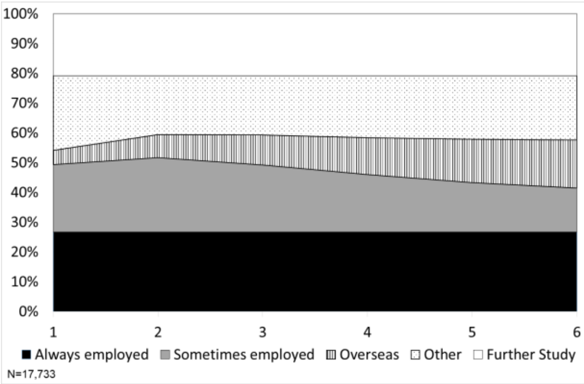
High STEM graduates



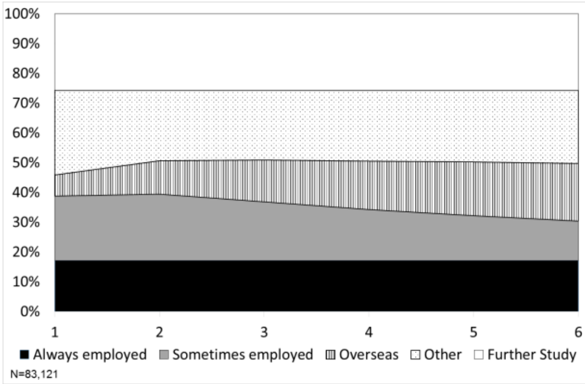
High non-STEM graduates



Low STEM graduates

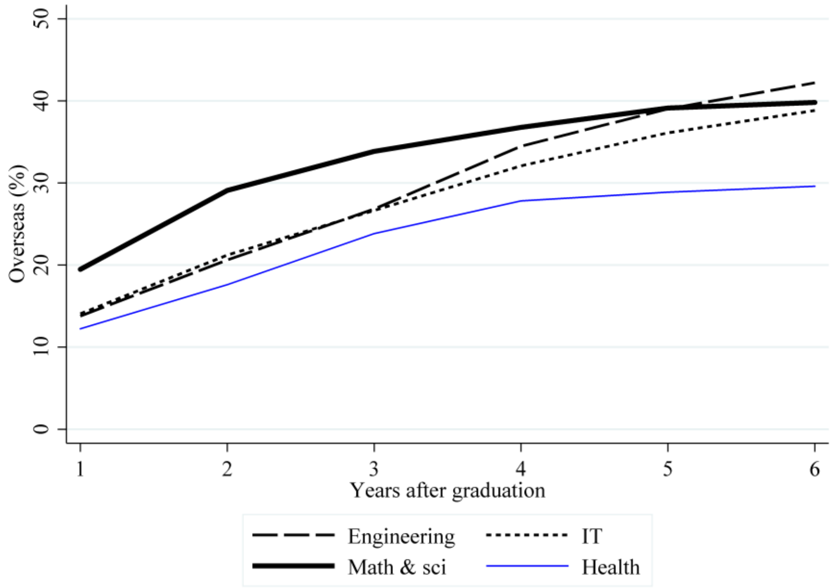


Low non-STEM graduates



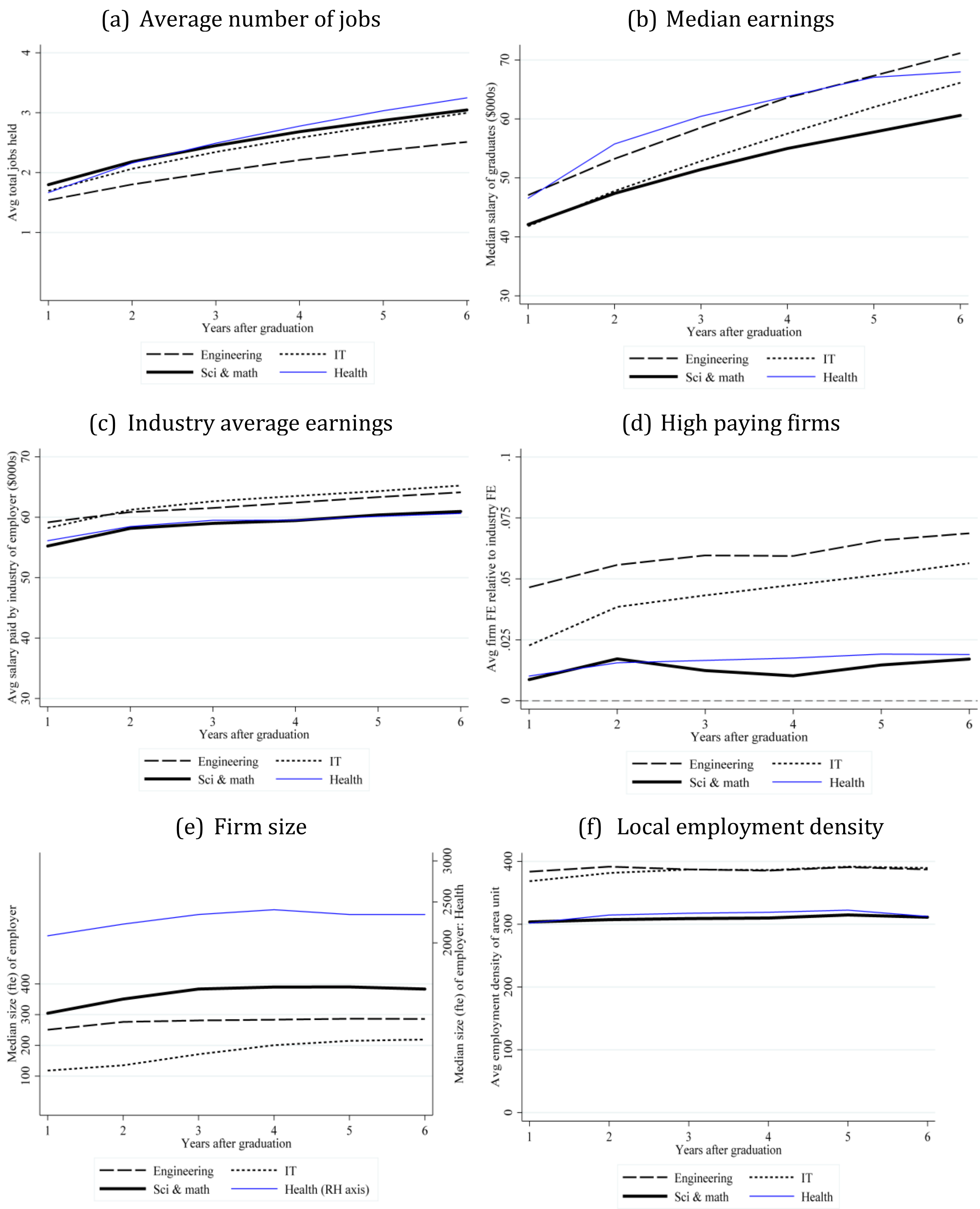
Notes: see the notes for Figure 1. A (rounded) total of 187,395 graduates (each followed for six years) are included in this figure (Population 1 in Table 1).

Appendix Figure 2: Proportion overseas, within high STEM + health



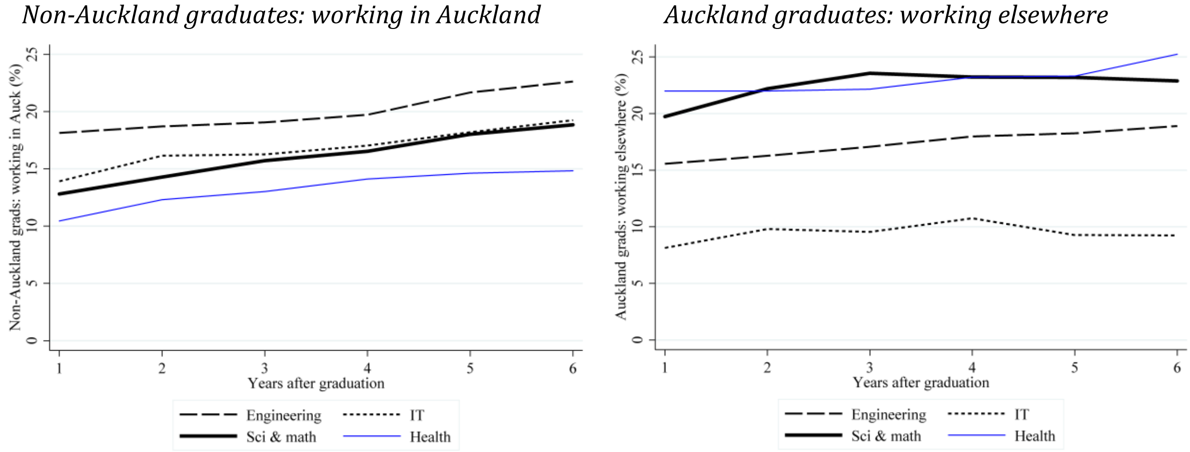
Notes: Limited to high (bachelor's and above) STEM and health graduates. Beyond this, see the notes for Figure 2.

Appendix Figure 3: Total jobs, within high STEM + health



Notes: Limited to high (bachelor's and above) STEM and health graduates. Beyond this, see the notes for **Error! Reference source not found.**.

Appendix Figure 4: Moving to and from Auckland: *high STEM + health graduates*



Notes: Limited to high (bachelor's and above) STEM and health graduates. Beyond this, see the notes for Figure 4.

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