MINISTRY OF BUSINESS, INNOVATION & EMPLOYMENT
HĪKINA WHAKATUTUKI

Labour market impacts of technology change

Evidence from linked employer-employee data

Corey Allan and Lynda Sanderson

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Authors

Corey Allan, Chief Economist Unit
corey.allan@mbie.govt.nz

Lynda Sanderson, Chief Economist Unit
Lynda.sanderson@mbie.govt.nz

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Ministry of Business, Innovation & Employment
PO Box 1473
Wellington 6140
New Zealand
www.mbie.govt.nz
0800 20 90 20
Media enquiries: media@mbie.govt.nz

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Abstract

Advances in robotics and artificial intelligence mean that tasks previously considered the domain of humans are able to be performed by machines, potentially displacing workers currently performing those tasks. The aim of this research is to explore whether we are beginning to observe the impact of automation in the New Zealand labour market. To this end, we examine the relationship between the degree of self-reported technology change and firm-level employment outcomes in New Zealand over the period 2005-2016. We use a combination of survey and administrative data in Stats NZ's Longitudinal Business Database and Integrated Data Infrastructure. We test whether firms that report undertaking major technology change differ from other firms in terms of their employment and wage growth, changes in the wage distribution, and changes in the qualifications structure of their workforce. The main finding is that firms experience more rapid employment growth following a major technology change. Where we do find evidence of changes in the qualifications structure of firm workforces, the changes are relatively small. Our estimates suggest that firms increase their demand for workers with university qualifications and there is some evidence they reduce their demand for workers with a post-school qualification. However these changes are relatively small, equivalent to between 0.5 and three workers in an average firm of 140 workers. The relationships are strongest among the small group of firms that report three major technology changes over a three year period and an organisational or process innovation.

JEL classification

J21; J23; J24; O33

Keywords

Technology change; skills; employment; qualifications; Business Operations Survey; Longitudinal Business Database

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1 Introduction

Many of us have in our pockets significantly more computing power than was used to place a man on the moon. The comparison between the modern smartphone and the IBM mainframes of the 1960s is just one of many examples showing the exponential growth in computing power over the last 50 years. Rapid advances in processing power and the digitisation and sharing of information fostered by the internet have the potential to transform our society and economy, creating new industries, products and services and driving future prosperity (see, for example, Rifkin 2011, Brynjolfsson & McAfee 2014). However, there are concerns around how these new technologies will affect the labour market and how the expected productivity gains will be shared.

Recent interest in the impacts of technology change on the New Zealand labour market is shown by a recent Productivity Commission inquiry into 'Technological change and the future of work' (New Zealand Productivity Commission 2020). The findings suggest that the uptake of new technologies in New Zealand is relatively low and that large-scale disruptions to the labour market are not imminent. The Commission recommends that New Zealand embrace new technologies to help drive productivity growth while putting the right policies in place to support workers that may be negatively impacted. The government also established the Future of Work Tripartite Forum in 2018 with representatives from business, labour unions, and government.[1] The Forum aims to support New Zealand businesses and workers to meet the challenges and opportunities presented in a rapidly changing world of work, including from technological change.

Increasing adoption of computer and digital technologies has been put forward as a possible explanation for trends in labour markets in the last 30-40 years.[2] These trends include an increasing share of workers with a university education, stagnating real median wages, and declining labour income shares.[3] The main finding from this literature is that new computer and digital technologies tend to replace workers in jobs with a lot of routine tasks, while complementing those in jobs with more problem solving, communicative or creative tasks (e.g. Autor et al. 2003; Acemoglu & Autor 2011). The continued growth in processing power, coupled with rapid increases in the amount of digitised information and advances in artificial intelligence mean that an ever growing range of tasks may be automated in the future (e.g. Brynjolfsson & McAfee 2014).

New Zealand has experienced some of the trends seen overseas. Our labour income share has declined since the 1980s (Rosenberg 2017), the share of university educated workers has increased substantially and real median wage growth has been low at around 1.3% per year (Maré, 2018).

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[1] More information on the Future of Work Tripartite Forum can be found at https://www.treasury.govt.nz/information-and-services/nz-economy/future-work-tripartite-forum

[2] See Katz & Autor (1999) for a summary of the earlier literature, and Card & DiNardo (2002) for a critique.

[3] Other explanations for some of these trends that have been put forward include the impact of trade liberalisation and import competition (e.g. Autor et al. 2013; 2016), changes in product market competition (e.g. Autor et al. 2020), and declines in worker power (e.g. Stansbury & Summers 2020).

This research considers whether we are beginning to see the effects of automation found in other advanced economies in the New Zealand labour market and whether this explains recent trends in the labour market. We do this by looking at the relationship between technology change and firm-level labour demand using the rich firm- and individual-level data available in Stats NZ's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). We consider the relationship between technology change and overall firm employment, average monthly earnings, within-firm wage dispersion, and the skill composition of a firm's workforce, measured by the qualification levels of employees.

Patterns consistent with the task-based model of the impacts of technology change are already evident in other countries. Autor & Price (2013) and Autor et al. (2003) document the decline in the importance of routine tasks and the increasing importance of non-routine tasks (particularly analytical and interpersonal tasks) in the US since the 1960s. Acemoglu & Restrepo (2020) look at local labour market impacts of a specific type of automation – industrial robots. They estimate that the equilibrium effect of adding one more industrial robot per thousand workers is to reduce the employment rate in the local labour market by between 0.18-0.34 percentage points and wages by 0.25-0.5%. Borjas & Freeman (2019) argue that, while the growth of industrial robots over the period 1996-2016 is too small to have had a major aggregate impact on wages and employment, continued exponential growth in the use of robots is likely to disrupt labour markets in the foreseeable future.

Evidence from firm-level studies is also consistent with the predicted effects of automation. These studies estimate the impact of introducing new technologies, innovations and organisational practices on wage-bill or employment shares of workers with different skill levels. This literature generally finds that introducing new technologies or organisational practices increases the wage-bill share of high-skilled workers while reducing the share of low-skilled workers (e.g. Caroli & Van Reenen 2001, Kaiser 2000, Evangelista & Savona 2003, Siegel 1998, among others). Occupation is typically used as the measure of skill in these firm-level studies. Bresnahan et al. (2002) show a complementarity between skilled labour and a combination of three related innovations: information technology, complementary workplace practices, and new products and services. Piva et al. (2005) find evidence of super-additive effects of both new technology and organisational innovations in the demand for skilled labour.

Fabling & Grimes (2016; 2019) are two recent New Zealand studies looking at the impact of ultra-fast broadband (UFB) adoption on the productivity and wages of New Zealand firms. Fabling & Grimes (2016) find that UFB adoption is associated with an increase in multi-factor productivity among the group of firms that implement complementary organisational changes designed to maximise the benefits of UFB. Firms that make no such complementary organisational changes don't experience a significant productivity boost. Fabling & Grimes (2019) show that, among continuing workers, the wage premiums associated with UFB adoption are concentrated among men with at least a post-school diploma or with a STEM qualification. These wage premiums are small, with estimates no greater than 2%. Women with the same qualifications do not receive a wage premium. They show that UFB is a specific source of skill-biased technological change and highlight the potential role of technology in the gender wage gap.

The studies cited above are backward looking i.e. have we seen impacts consistent with the automation of routine tasks? Considerable effort has also gone into projecting the fraction of employment in jobs that are potentially amenable to automation in the future. A seminal example is Frey & Osborne (2017), who estimate that 47% of current US employment work in jobs that may be amenable to automation in the coming decades. NZIER & CAANZ (2015) use the same methodology as Frey & Osborne (2017) and get an estimate of 46% of current NZ employment. Other recent reports by Kiernan (2018) and PriceWaterhouseCoopers (2018) provide estimates of 31% and 24% of jobs in NZ being potentially automatable, respectively. OECD estimates using the Survey of Adult Skills tend to be lower, with an average of 14% of workers in jobs that are amenable to automation across the OECD and around 12% in NZ (Nedelkoska & Quintini 2018). Other OECD work finds that, on average, 46% of people employed across 20 OECD countries are in non-routine or low routine-intensive occupations, with significant variation across countries (Marcolin et al. 2016). AlphaBeta (2016) estimate that 70% of the impact of automation in Australia will be the changing task composition within jobs (i.e. spending less time on automatable tasks), while the remaining 30% will come from job reallocation.

In this paper, we compare changes in overall employment, the earnings distribution, and relative skill demands between firms that report undertaking major technology change to those that report no change using a simple event-study approach. International firm-level studies typically do not examine the overall employment effect, which is important for understanding the mechanics behind any shifts in skill demand. We consider both the timing and persistence of such changes, as well as the cumulative effects over a three year period.

Major technology change is relatively rare in our sample, with between 6% and 9% of firms reporting major technology change in any given year, compared to 48%-58% reporting minor technology change. These firms account for between 10% and 12% of employment in our sample. In line with New Zealand Productivity Commission (2020), we do not see any evidence that the pace of technology adoption is increasing. However, the impacts of COVID-19 may have spurred more businesses to adopt new technologies to help them cope with the shock (McKinsey 2021).

The results do not show evidence of significant job displacement or skill/routine-biased technology change occurring within firms. We find a strong, positive relationship between reported technology change and employment growth, but little evidence of a relationship between reported technology change and changes in firms' earnings distributions or the skill composition of their workforces. The relationship is strongest for the small subset of firms that repeatedly report undertaking major technology changes. These firms see an increase in the share of the wage-bill going to workers with an honours degree or above and there is some evidence of a decline in the share of the wage-bill going to workers with a post-school qualification. Where we do find a statistically significant relationship between technology change and skill composition, the estimated coefficients are relatively small, equivalent to between 0.5 and 3 workers at the average wage in a firm with 140 workers.[4] Firms that undertake a major technology change tend to have a more highly qualified workforce, suggesting that the

[4] These small estimated effects are likely overestimates of the number of extra workers as university-qualified workers likely earn more than the average firm wage.

primary impact of technology change over our sample period is a reallocation effect. Technology change allows more highly-skilled firms to expand. Overall, we conclude that technology change has not had a major impact on the New Zealand labour market in the 15 years to 2016, although there is some evidence that the relationship between technology change and labour market changes is strengthening over time.

The rest of the paper is organised as follows: section 2 gives more details of the task-based framework for thinking about the impacts of technology change, section 3 provides details of the data used in this study, section 4 describes our empirical approach, section 5 presents our results, and section 6 concludes.

2 How new technologies impact jobs

The dominant framework for thinking about the impacts of technology change on the labour market focusses on tasks. In this framework, production is viewed as a series of tasks that need to be completed (e.g. Autor et al. 2003, Acemoglu & Autor 2011, Acemoglu & Restrepo 2018). Combinations of 'traditional' capital (e.g. land and buildings) and human or machine labour are used to complete tasks. The choice between human and machine labour depends on their relative productivities and prices. New technologies alter the relative productivities of human and machine labour, as well as the relative price of human to machine labour. Tasks that are most likely to be automated (i.e. switch from being performed by human labour to machine labour) are those that are routine. These are tasks which require following logical steps with clear rules and are the easiest to codify in computer language.

The impact of new technologies on different types of workers depends on how tasks are grouped together into jobs and the types of people who work in those jobs. If routine tasks tend to be grouped into jobs filled by low-skilled people, advances in technology will negatively impact low-skilled workers while benefitting highly skilled workers i.e. skill-biased technological change. If routine tasks are grouped into jobs that tend to be performed by those in the middle of the skill distribution, this can lead to 'job polarisation', where the number of people working in medium skilled, middle income jobs declines and employment in high- and low-skilled jobs increases (Acemoglu & Autor 2011). Acemoglu & Restrepo (2018b) contrast the wage, employment, and inequality implications of the cases when automation impacts low-skilled vs. high-skilled occupations.

Acemoglu & Restrepo (2018) discuss four impacts of new technologies on the labour market in the context of a task-based model:

- labour displacement
- productivity improvement
- capital accumulation and automation deepening
- the creation of new labour-intensive tasks

In their framework, the displacement effect of automation reduces the demand for labour, thereby lowering wages and employment. The productivity effect and capital accumulation act to offset the decrease in demand for labour caused by the displacement effect. Higher output per worker as a result of automating particular tasks allows the economy to expand, increasing the demand for labour in non-automated tasks. The productivity effect also triggers capital accumulation through increasing the demand for traditional capital, which will also raise the demand for labour. Automation deepening relates to improvements in the productivity of machines performing tasks that have already been automated, delivering productivity benefits without the displacement of workers (e.g. faster robots, more efficient AI algorithms).

The productivity, capital accumulation and automation deepening effects by themselves are unlikely to offset the displacement effect. The authors argue that the most powerful countervailing effect is the creation of new labour-intensive tasks allowed by the new technologies, which they term the reinstatement effect. Even in the presence of these countervailing forces to the displacement effect of automation, they argue that the adjustment to a rapid rollout of automation could be slow and painful, highlighting the disruptive nature of new technologies. However, history shows us how powerful the creation of new labour-intensive tasks is in responding to advances in technology. Acemoglu & Restrepo (2018) briefly discuss the large-scale automation of tasks in textiles, metals, and agriculture in the 19th and 20th centuries and the subsequent increase in the number of tasks in factory work, engineering, repair, back office, management, sales, design, and finance that generated demand for displaced workers.

3 Data and descriptive analysis

3.1 Data

Our data is sourced from Stats NZ's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). The LBD is a collection of administrative and survey data on firms in New Zealand (see Fabling & Sanderson 2016 for further detail on the structure and content of the LBD). Our sample of firms is drawn from the Business Operations Survey (BOS), which is an annual survey of private-for-profit firms with a rolling mean employment (RME) of at least six.

The BOS collects information on a range of business practices, including innovation, international engagement, ICT use, strategic planning, and the firms' perceptions of their business environment. The question of primary interest in this study is shown in Figure 1. This question appears in module A of the BOS, which contains a consistent set of questions that are asked every year. As very few respondents indicate a complete change, we combine major and complete change in our analysis.

Figure 1: Technology change question from the Business Operations Survey

24 Over the last financial year, to what degree did this business's technology change?

1 not at all
2 to a minor degree
3 to a major degree
4 completely
5 don't know

A2400

Each BOS survey has between 5000 and 7000 firm responses (out of a total population of around 35,000-45,000) and contains a longitudinal element.[5] Our BOS data covers the period 2005-2016 and we have a sample of 75,738 firm-year observations on 15,897 firms. As the BOS population is restricted to firms with at least 6 RME, the total population of firms from which the sample is drawn is a small fraction of all firms in New Zealand. In 2015, the BOS population consisted of 39,000 firms out of a total population of 507,000 firms in New Zealand.[6] Despite representing a small fraction of NZ firms, in 2015 the BOS population collectively employed 1.27 million people, or roughly 55% of the official employment count. Within this population, total RME in the

[5] The BOS sample is a stratified random sample from a population of firms that numbers between 35,000 and 45,000. The sample is stratified according to industry and firm size. As the BOS is a Stats NZ survey, it has a very high response rate at over 80%. To increase the longitudinal nature of the survey, StatsNZ periodically include extra firms as a top up to the panel. We identify firms in BOS using the permanent enterprise number (PENT), which corrects for statistical breaks in firm identifiers over time (Fabling 2011).

[6] Source: New Zealand Business Demography Statistics: At February 2018, Table 3. https://www.stats.govt.nz/information-releases/new-zealand-business-demography-statistics-at-february-2018

overall BOS sample is between 500,000 and 600,000 workers per year, approximately 20-25% of the official employment count.[7]

We identify individuals working at BOS firms using the labour table of Fabling & Maré (2015).[8] This contains monthly information on employment relationships and earnings. We identify 2.5 million individuals that work at a BOS firm over the study period and derive average monthly earnings, total annual earnings, and job tenure for individual-firm-year observations. We exclude working proprietors as we do not have earnings information for these workers. Working proprietors make up a very small fraction of total labour in our sample of BOS firms.

We use an individuals' highest qualification as a proxy for skill. Our main source of data for qualifications is the 2013 Census, which asks respondents resident in New Zealand on census night the level of their highest qualification. As this excludes people who were not in the country on 5 March 2013, we supplement the census qualification data with administrative data on course completions from the Ministry of Education. This provides information on the type and level of qualification and the date completed. The data captures all qualifications completed in New Zealand since 1994 for tertiary institutions, 2003 for Industry Training Organisations (ITOs), and 2007 for secondary schools. People who completed their qualifications prior to these dates or those who have overseas qualifications are not captured by the administrative data. As we have only a snapshot of qualifications for much of the population, we use highest reported qualification over all time as our measure of skill, rather than a point-in-time measure of qualifications in the years in which workers are employed by BOS firms. While this will overstate the qualifications of some workers, particularly workers who are new to the labour market, it provides a simple measure of "potential skill", based on the idea that the propensity to undertake higher qualifications is strongly correlated with innate ability (e.g. Heckman et al. 2006).[9] Where people have qualification information in both sources, we take the highest qualification across the two sources.[10] Even after combining census and administrative information, 20% of the sample has no qualification information. These individuals are included in the analysis as a separate group (missing qualifications), which may include a diverse range of skill levels.[11] We do this to ensure we are accounting for the entirety of firm wage bills.

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[7] One key employer group which is excluded from the BOS is the public sector. Governments are also looking for ways to reduce costs and improve the quality of services they deliver and are adopting new technologies as part of these efforts. It is likely that technology change has similar impacts in both the government and non-government sectors, but data limitations prevent us from examining the impacts for government employees.

[8] The main source of this data is the Employer Monthly Schedule (EMS). The EMS is the monthly reporting of individual incomes by firms for the administration of NZ's PAYE personal income tax system.

[9] We may also understate the qualifications of individuals who completed higher level qualifications outside of New Zealand following the census (who are therefore not captured by the administrative data) and the "potential skill" of those who attained higher qualifications after the end of our sample period.

[10] 42% of highest qualifications observations come from census and 38% come from administrative sources.

[11] 63% of individuals with missing qualifications are migrants, so are likely to have qualifications from offshore, but aren't captured in either the Census or the administrative data.

We aggregate the employment, earnings, and qualification information to the firm level to calculate our firm-level employment outcomes. Our measures of overall employment are rolling mean employment (RME) and the total wage-bill. These outcomes are important for understanding whether technology change is affecting the overall demand for labour.[12] We calculate average monthly earnings at the firm and the within-firm standard deviation in (log) average monthly earnings to test for a relationship between technology change and the within-firm earnings distribution.[13] Our measures of the skill composition of firm workforces are the share of the wage-bill going to workers with different qualifications. Wage-bill shares are the standard measure used in the firm-level technology change literature (e.g. Caroli & Van Reenen 2001, Evangelista & Savona 2003, Piva et al. 2005). We calculate the wage-bill shares for five groups of qualifications, plus a residual category for those with missing qualification information. The qualifications categories are no qualifications, high-school qualifications, post-school qualifications, bachelor's degree, honours degree or above, and missing qualifications. We drop observations with insufficient information to calculate the level and change in all of the outcome measures.[14] This leaves us with a sample of 74,193 observations on 15,474 firms.

In contrast to much of the international literature, our main measure of skill is qualifications rather than occupation, as longitudinal occupation information is not available at the individual level for the majority of the population.[15] We make use of information from the BOS on the occupational composition of the workforce as reported by the firm as a robustness test. However this data does not provide a clear view of changing occupational structures due to the highly aggregated nature of the categories, in which many occupations with different skill or qualifications requirements, and likely different task compositions, are combined into a single 'other' category.[16]

In order to control for demand conditions and changes in capital intensity (which may be directly associated with technology change – see Appendix 1), we link the employment data to firm financial information from the 2018 update of the productivity dataset described in Fabling & Maré (2015; 2019). The data combine information from the Annual Enterprise Survey (AES) and administrative tax data (IR10 financial statement summaries) in a consistent form and have been used extensively to estimate production functions and study the drivers of firm-level productivity in New Zealand (e.g. Fabling & Grimes 2016, Wakeman & Conway 2017, Chappell & Jaffe 2018).

[12] They are also important for interpreting the context in which any changes in workforce composition are occurring, as these measures form the denominator of the shares.
[13] We exclude the first and last months of employment at the firm from the earnings calculations. Earnings in the first and last months of employment are unlikely to accurately reflect a person's regular earnings due to starting or leaving partway through a reporting month or payments associated with starting or leaving a job (signing bonus, payout of annual leave etc.).
[14] The observations we drop are mostly small, young firms.
[15] While Census does include occupation information, this is only a snapshot.
[16] The occupational groupings collected in BOS are 'Professional/Managers' (ANZSCO divisions 1 and 2) 'Technicians' (ANZSCO division 3), 'Trades workers' (ANZSCO division 3), and 'Other'. Other includes ANZSCO divisions 4-8, combining, for example, community and personal service workers (mid-skilled occupations) with labourers (low-skilled occupations).

This link further reduces the estimation sample, as not all firms in the BOS have useable financial information. Firms may not be included in the AES sample and may use alternative methods to satisfy tax reporting requirements to Inland Revenue. Some have missing information or internal consistency issues in their AES or IR10 forms. We have financial information for 70% of our overall BOS sample.[17]

Finally, as the goal of the paper is to examine changes in technology and workforce characteristics at the firm level, we further restrict our estimation sample to firms with at least three consecutive years of BOS and four years of financial information. The impacts of technology change are not necessarily instantaneous or one-off. There may be lags in when the effects become apparent and they may persist or accumulate over time (i.e. a firm may take time to discover what their new desired skill composition is and adjustment to the new desired skill composition may be slow). Placing longitudinal restrictions on our sample enables us to investigate these patterns. Our main estimation sample contains 23,214 observations on 5,526 firms, roughly 1/3 of our BOS sample with sufficient employment information. These firms have aggregate employment of between 300,000 and 350,000, roughly 55% of the total employment in the overall BOS sample. In robustness checks we also consider a sample of firms with at least five years of BOS and financial growth information.

Table 1 shows summary statistics comparing our main estimation sample with the overall BOS sample. Rates of major technology change are lower in the estimation sample than the overall sample at 7.3%, while rates of reported minor technology change are higher. On all measures of firm size, firms in our estimation sample are larger. Value added in our estimation sample is nearly $20 million, compared with $14 million in the overall sample. Both average employment and the average wage-bill are significantly larger in the estimation sample. Average monthly earnings are also higher in the estimation sample, at $4000 compared to $3,700 in the BOS sample. Firms in the estimation sample have a greater share of the wage-bill going to workers with no, high school, or post-school qualifications and a lower share going to those with either a bachelor's degree or a higher degree.

[17] In the wider firm population, around 30% of all private-for-profit firms each year have no production information (Fabling & Maré 2019).

Table 1: Summary statistics on technology change, firm performance, and workforce characteristics

	Full BOS/employment (n=74,193)	Main estimation sample (n = 23,214)
Technology change – proportion of observations		
Major technology change, %	8.1%	7.3%
Minor technology change, %	60.6%	63.5%
Firm performance –sample average across firms		
Value added*	$14,048,200	$19,792,700
Value of capital services*	$3,694,200	$5,179,500
Total wage-bill	$4,814,400	$8,010,800
Employment (RME)	96	144
% of employment in BOS sample	100%	55.9%
Workforce characteristics – sample average across firms		
Avg. monthly earnings	$3,688	$4,062
Std. dev (log) avg. monthly earnings	0.692	0.662
% wage-bill no qualifications	10.8%	11.3%
% wage-bill high school qualifications	33.3%	34.4%
% wage-bill post school qualifications	24.5%	25.1%
% wage-bill bachelor's degree	13.8%	12.8%
% wage-bill honours or above	6.5%	5.9%
% wage-bill missing qualifications	10.9%	10.4%

Notes: The number of observations has been randomly rounded to base 3 for confidentiality purposes. Average value added and the value of capital services in the full BOS/employment sample is calculated for the firms with non-missing financial information (n = 51,648 for these variables).

3.2 Descriptive analysis

3.2.1 Population statistics

We first look at trends in the responses to the technology change question and variation in responses across industries. Figure 2 shows the percentage of firms in the BOS population giving each response to the technology change question (solid lines) and the fraction of employment in the BOS population that these firms account for (dashed lines).[18]

Minor change is the modal response to the technology change question, with 49-58% of firms giving this response each year. 32%-45% of firms report no change, while 5-9% of firms report major or complete technology change. Firms that give a positive response to the technology change question (minor or major/complete) tend to be larger, evidenced by these firms accounting for a larger share of employment than their share of the firm population. Each year, between 62% and 69% of employees are in firms that report minor technology change, while 10-12% of employees are in firms that report major technology change. Rates of minor and major technology change fell during the Global Financial Crisis (GFC) and have recovered since. However, there is

[18] Figures 2 and 3 report population statistics. These are calculated using the full sample of BOS respondents (response code R) and the BOS population weights.

little evidence of an increasing long-run trend in the fraction of firms that report undertaking any level of technology change.

Figure 2: Percentage of firms and employment at each level of technology change over time

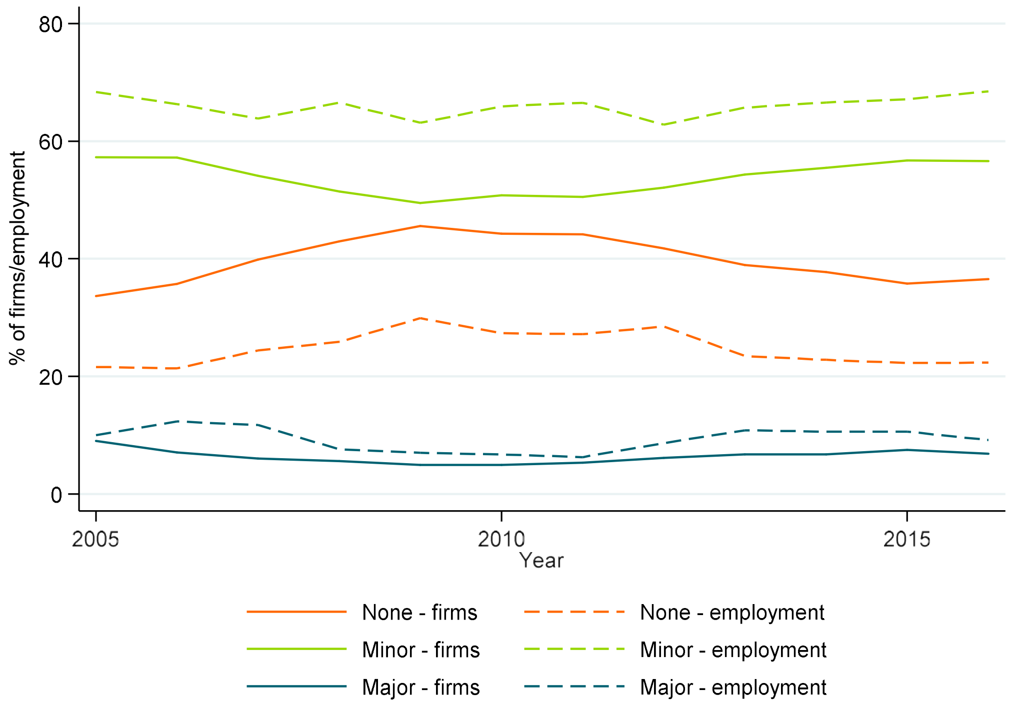
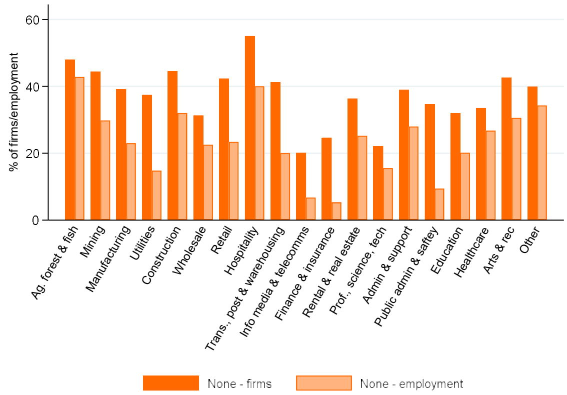


Figure 3 shows the variation in the extent of technology change by industry, again along with the share of BOS employment in these firms. Panel A shows the variation in the percentage of firms reporting no technology change, panel B the percentage of firms reporting minor technology change, and panel C the fraction of firms reporting major or complete change.

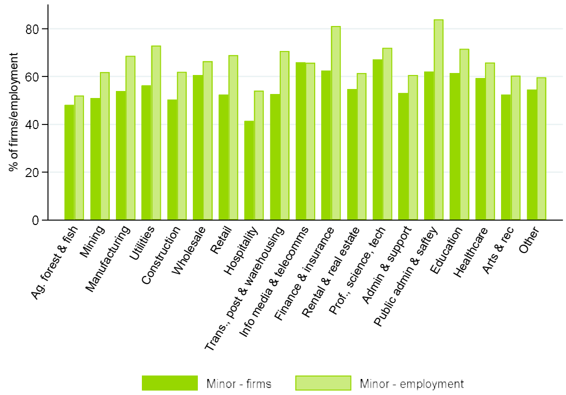
There is significant variation across industries in the likelihood of reporting some level of technology change. Rates of minor technology change range from 40% in hospitality to 67% in professional, scientific and technical services. For major technology change, rates vary between 3% in hospitality and agriculture, forestry and fishing to 14% in information media and telecommunications. The finding that larger firms are more likely to report some level of technology change holds for all industries.

Figure 3: Percentage of firms and employment by answers to the technology change question

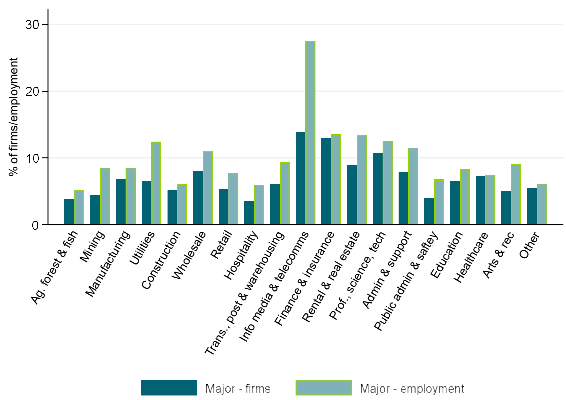
Panel A – no technology change



Panel B – minor technology change



Panel C – major/complete technology change



3.2.2 Repeated technology change

We next look at the incidence of repeated technology change in our analysis sample. Figure 4 shows the percentage of firm-year observations associated with different combinations of major and minor technology change. Panel A considers repeated major change, while panel B considers combinations of major and minor change.

The vast majority (82%) of observations are of firms that report no major change over a three year period. Of the rest, 75% report one instance of major technology change. Only 1% of observations are firms reporting major change in each year of a three year period.[19]

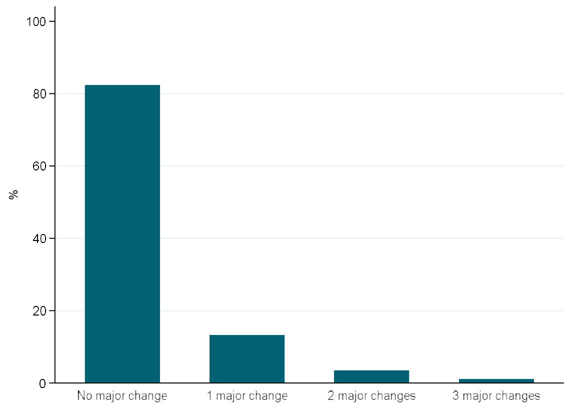
For firms that report no major technology change, 84% report at least one instance of minor technology change over a three-year period, with 47% reporting three instances of minor change. Instances of minor technology change are common for firms with at least one instance of major technology change. When major technology change occurs

[19] In some cases, these may represent one major change that is implemented over a number of years rather than separate instances of technology change.

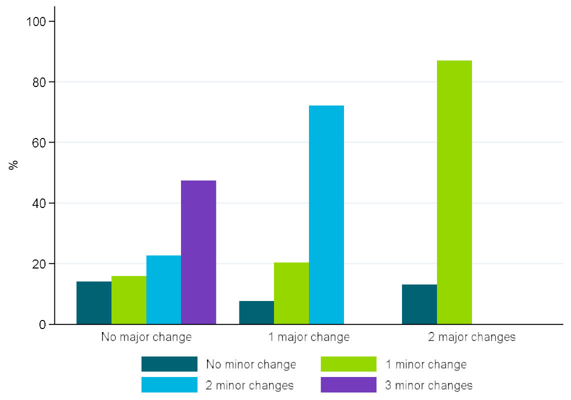
in a three year period, over 85% of firms also report at least one instance of minor technology change within the same period.

Figure 4: Incidence of repeated major technology change (panel A) and combinations of major and minor change (panel B) over a three-year period (n=23,214).

Panel A – repeated major technology change



Panel B – combinations of major and minor change



3.2.3 Cohort trends

We now look at the evolution of our employment variables over time for a cohort of firms present in the BOS sample in 2012. [20] We compare the trends over the period 2010-2015 in total employment, total wage-bill, the wage distribution, and the qualifications composition for firms that report a major technology change in 2012 (t=0 in the figure) and those that don't.

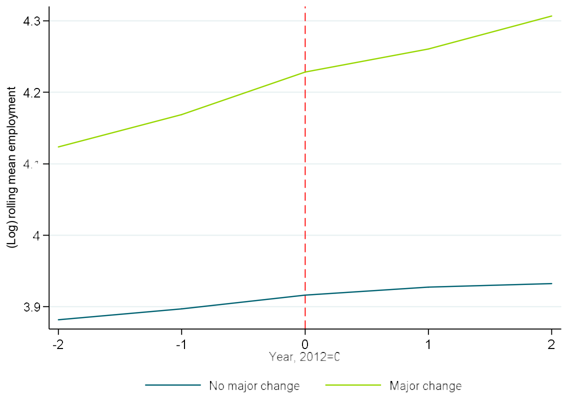
Figure 5 plots the overall employment measures. We see that firms reporting major technology change are much larger, both in terms of employment (panel A) and the total wage-bill (panel B), and have higher average monthly earnings than firms that report no change (panel C). They also have a slightly wider earnings distribution prior to reporting a major technology change (panel D).

Growth in employment and the total wage-bill appears to be slightly faster in firms that report major technology change than firms that don't and there doesn't appear to be any marked change in the growth rates in the years following a major technology change. There is very little apparent difference in the growth rates of average monthly earnings between firms that report a major technology change and those that don't.

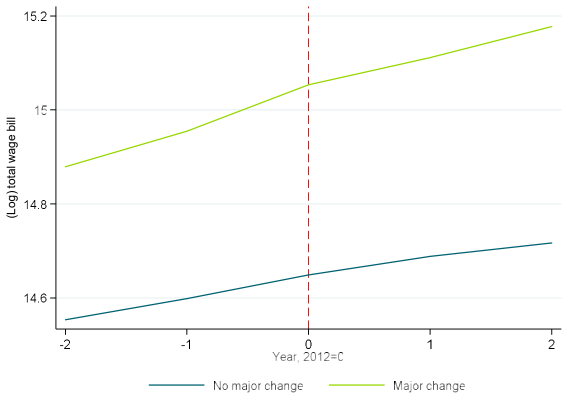
[20] The cohort is defined as firms that were present in 2012, gave a valid answer to the technology change question, and were present in the BOS sample each year over the period 2010-2014

Figure 5: Trends in employment and earnings distribution for 2012 cohort

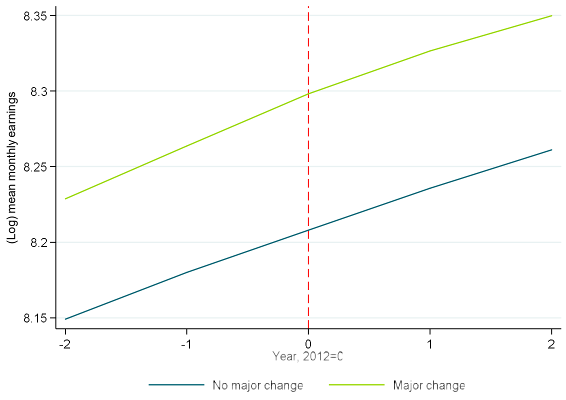
Panel A: Employment



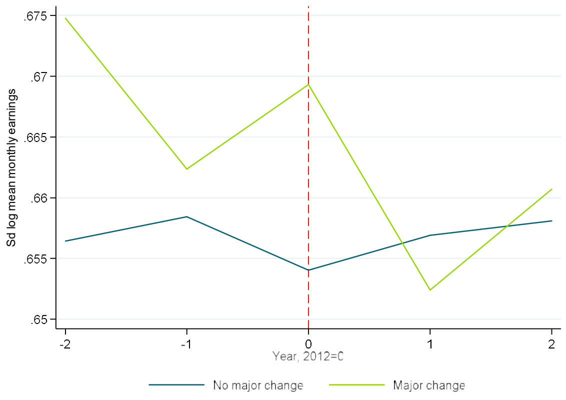
Panel B: Total wage-bill



Panel C: Average monthly earnings



Panel D: Std. deviation log monthly earnings

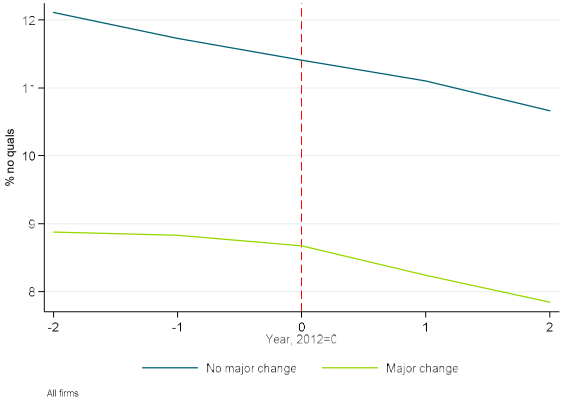


We do see differences in the trends for the standard deviation of log monthly earnings between firms that report a major technology change and those that don't. There is a pronounced downward trend over the five years for firms that report major technology change, while those that don't report major technology change have a relatively flat trend. There is a substantial decline in the standard deviation in the year following a major change, which is partly reversed in the second year. This decline appears to have begun before a change was reported so it is not clear if the technology change has played a role in the changing earnings distributions from this simple comparison.

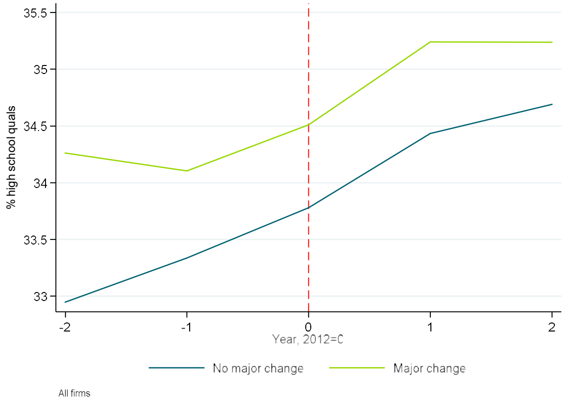
Figure 6 plots trends in the qualification wage-bill shares. Here we see some more marked differences between firms that report a major technology change and those that don't. Growth in the share of the wage-bill going to workers with high-school qualifications was similar to firms that didn't report a major change between t-1 and t+1 (panel B). In the second year following a change, growth in this share reduces to essentially zero for firms reporting a major change. Firms that don't report a major change still see this share growing.

Figure 6: Trends in qualification wage-bill shares for 2012 cohort

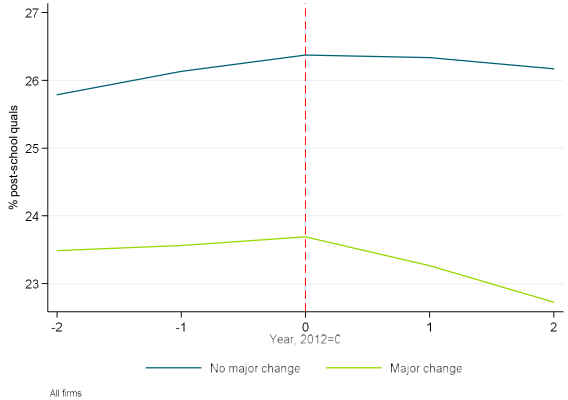
Panel A: No qualifications



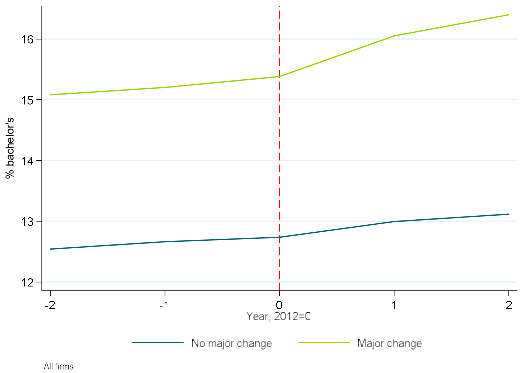
Panel B: High-school qualifications



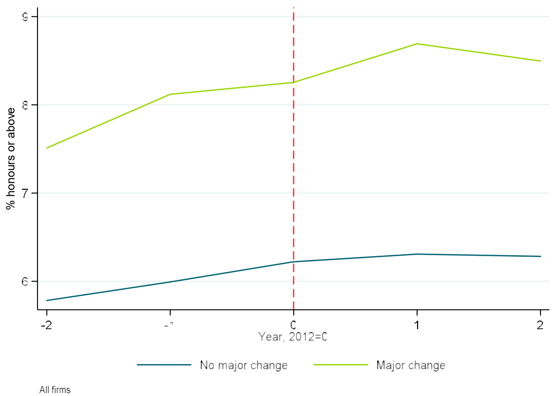
Panel C: Post-school qualifications



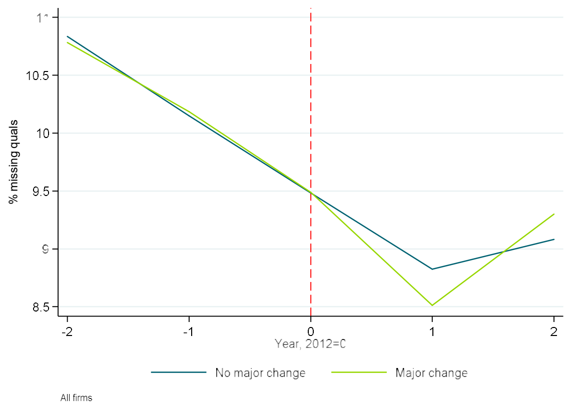
Panel D: Bachelor's degree



Panel E: Honours or above



Panel F: Missing qualifications



Growth in the share of the wage-bill going to workers with post-school qualifications is slightly lower prior to the change for firms that report a major change (panel C). In the years following a change, this share begins to decline and is approximately 0.5pp lower two years following the change. For firms that don't report a change, this share flattens out before beginning to decline slightly, although the magnitude of the decline is larger for firms that report a change. Trends in the share of the wage-bill going to workers with a bachelor's degree are similar in the years prior to a change, before growth in the share accelerates after firms report a major change (panel D). In the two years following a change, the share increase by around 1pp. Firms that don't report a major change see very little change in the growth rate over the five year period.

Overall, we don't see large changes in the overall employment outcomes after firms report a major technology change. These firms had more rapid employment growth prior to reporting such a change. We see no change in growth of average monthly earnings, which was similar to firms that don't report a change. We do see some differences in the evolution of qualification structure of firm workforces. The rate of upskilling seems to accelerate, particularly for workers with a bachelor's degree, while the share of the wage-bill going to workers with a post-school qualification begins to decline. This analysis, while for a single cohort of firms, gives us some indication of the types of results to expect in our more formal analysis.

4 Empirical methodology

4.1 Correlates of technology change

We begin by examining the firm characteristics that are associated with a higher (lower) likelihood a firm reports undertaking major technology change. The purpose is twofold: to get a better (descriptive) understanding of some of the firm-level factors that are associated with a major technology change, and to test whether the historic evolution of our dependent variables (employment, earnings distribution, qualifications distribution) predict subsequent major technology change.

We estimate an ordered logit model of the form:

$$\Pr(\Delta Tech_{it} = m) = X_{i,t-1}\beta + Z_{i,t-1}\gamma + \theta_{jt} + \varepsilon_{it} \quad (1)$$

where m represents the different responses to the technology change question (no change, minor change, major/complete change), X is a vector of continuous covariates, Z is a vector of binary covariates, and θ_{jt} is a set of industry*year dummies. The continuous covariates include the log of value added, the value of capital services, employment, labour productivity, and the qualification structure of the firm workforce. The qualifications structure is included in both levels and changes. [21] Binary covariates include whether the firm is an exporter, under (partial) foreign ownership, whether they have innovated or performed R&D, indicators for their answer to the BOS competition question, indicators for their answer to the age of core equipment question, and whether they report hiring difficulties.[22]

We use lagged values of the independent variables to lessen the impact of reverse causality on the results. Using contemporaneous values would make it more difficult to separate whether the specific variable (e.g. % of workforce with a bachelor's degree) predicts technology change or changes as a result of technology change.[23]

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[21] We tested whether lagged first differences of the other continuous variables predicted any degree of technology change. These variables were jointly insignificant so were dropped from the results presented in section 5.

[22] The competition question asks respondents to describe the business's competition as either a captive market, a market with one or two competitors, many competitors with several dominant, or many competitors with none dominant (omitted category). The core equipment question asks firms to compare their equipment to the best commonly available with the options fully up to date (omitted category), up to four years behind, four to 10 years behind, or more than 10 years behind. Hiring difficulties are defined by whether a firm reports moderate or severe difficulties in recruiting new staff in the following occupational groups: managers and professionals, technicians and associated professionals, tradespersons and related workers, all other occupations. Separate dummies are included for each occupational group.

[23] Using lagged values reduces the influence of reverse causality, but does not eliminate it. For example, a firm may make changes to its workforce composition in anticipation of a planned major technology change.

4.2 Employment impacts

We then look at the relationship between technology change and our employment variables. Our empirical methodology is descriptive in nature. We do not have a source of exogenous variation in technology change that we can exploit to identify causal effects. We therefore test for differences in the trajectories of various employment outcomes between firms with different levels of reported technology change using an event study approach.

Our starting point is the simple equation:

$$y_{it} = \alpha Tech_{it} + \gamma \ln VA_{it} + \delta \ln K_{it} + \eta_i + \varepsilon_{it} \tag{2}$$

where i, and t denote firm and year, respectively. y is one of: log RME, log total wage-bill, log average monthly earnings, the standard deviation of log monthly earnings, or one of the six qualification wage-bill shares. $Tech$ is a variable describing the technology 'vintage', VA is value added (gross output less intermediate expenditure), K is the value of capital services, η_i is a correlated firm fixed-effect, and ε is the error term.

We include value added as a proxy for the demand conditions facing a firm. We want to separate the effect of technology on labour demand from any change induced by differences in demand conditions. We include the value of capital services as a further control variable. We show in Appendix A that answers to the technology change question are related to additions to firm capital stocks. Failing to control for capital could then lead us to conflate technology-induced changes in labour demand with a more general relationship between the level of capital and labour demand. Equations of this form, including value added and capital as controls, are common in the firm-level technology change literature (e.g. Piva et al. 2005, Bratti & Matteucci 2005, Aubert et al. 2006).

For our first specification, we transform equation 2 by taking first differences. We do this because the survey question we use to measure technology is inherently a change question. Estimating the equation in differences also eliminates the correlated firm fixed effects and is the typical approach in the firm-level impacts of technology change literature (e.g. Caroli & Van Reenen 2001, Aubert et al. 2006).

Our first specification considers the timing and persistence of the effect of technology change on employment outcomes. In addition to taking first differences, we also add lags of the independent variables. The equation we estimate is:

$$\begin{aligned}\Delta y_{it} = &\sum_{s=0}^{2} \alpha_{1s} \Delta Tech\, maj_{i,t-s} \\ &+ \sum_{s=0}^{2} \beta_{1s} \Delta Tech\, minor_{i,t-s} \\ &+ \sum_{s=0}^{2} \gamma_{1s} \Delta \ln VA_{i,t-s} + \sum_{s=0}^{2} \delta_{1s} \Delta \ln K_{i,t-s} + \mu_{jt} + \varepsilon_{it}\end{aligned} \tag{3}$$

where Δ is the first difference operator, $Tech\ maj$ is a dummy variable equal to one if a firm reported a major technology change between $t-1$ and t, $Tech\ minor$ is similarly defined for firms that reported a minor technology change, and μ_{jt} are a set of industry*year dummies. All other variables are the same as in equation 2.

We are primarily interested in the α_{1s} coefficients, which tell us whether employment, earnings, or skill composition are changing more or less in firms reporting technology change compared to firms that report no change. We control for whether a firm reported minor technology change to ensure that the omitted category is firms that report no change in technology. This specification gives us insight into whether technology change has a temporary or persistent relationship with employment outcomes, and also how long after a change the relationship becomes evident.

We estimate our first specification on the sample described in section 3.1 over the period 2007-2016. This sample includes firms that report multiple instances of major technology change. This means the coefficients on lagged major technology change may be capturing a combined effect of repeated technology change, rather than the timing of effects from a single instance of major change. To better isolate the timing of any effects, we also estimate the model on a restricted sample that excludes firms that report multiple instances of major technology change. We also split our sample into two time periods, 2007-2011 and 2012-2016 to see whether the relationship between technology change and employment outcomes has changed over time.

To get a better idea of whether firms that report multiple instances of major technology change have a different experience than those reporting a single instance, we estimate a slightly different model on two cohorts of firms, those present in 2006 and in 2012.[24] We then follow these firms for three years. For these cohort regressions, we transform equation 2 by taking a long difference:

$$\begin{aligned}\Delta^l y_{it} = {} & \alpha_{21} 1\ Major_{it} + \alpha_{22} 2\ Major_{it} + \alpha_{23} 3\ Major_{ij} + \beta_{21} 1\ Minor_{it} \\ & + \beta_{22} 2\ Minor_{it} + \beta_{23} 3\ Minor_{it} + \gamma_2 \Delta^l \ln VA_{it} \\ & + \delta_2 \Delta^l \ln K_{it} + \lambda_{jt} + \omega_{it}\end{aligned} \tag{4}$$

where Δ^l denotes a long difference, $1\ Major$, $2\ Major$, and $3\ Major$ are dummy variables equal to one for firms that report one, two, or three major changes over a three year period, respectively. $1\ Minor$, $2\ Minor$ and $3\ Minor$ are similarly defined for minor technology change. λ_{jt} are industry*cohort dummies, ω is an error term, and all other variables are the same as in equations 2 and 3. We estimate equation 4 using the combination of the two cohorts and on each cohort separately.

We are again interested in the α_{2s} coefficients. These tell us the difference in outcomes for firms that reported one, two, or three instances of major technology change over the three year period, compared to firms that reported no instances of major or minor technology change. We then compare the α coefficients to look at the cumulative impact of repeated major technology change.

We extend our basic specifications to test whether firms that make other organisational changes alongside a major technology change experience different outcomes. Other

[24] These cohorts allow for a pre and post GFC comparison and to minimise the confounding impacts of the GFC. A large number of firms in the 2006 cohort are also present in the 2012 cohort.

research has shown that technology change and associated organisational changes are complements (e.g. Fabling & Grimes 2016, Piva et al. 2005). We show in Appendix A that firms that report major technology change are significantly more likely to report undertaking any kind of innovation, and organisational or process innovation in particular. We include a measure of organisational and process innovation from the innovation module of the BOS and interact this with our major technology change dummies.[25] This specification includes dummy variables for major technology change only, organisational or process innovation only, and major technology change *and* organisational or process innovation.[26]

We also run a number of robustness tests. First, we rerun our main specification on a subsample of firms with a longer BOS history, firms with at least one continuous five-year spell, as opposed to three years in our main sample. Second, we replace the qualification wage-bill shares with employment shares to get a better idea of the extent to which any patterns we observe are due to changes in employment or changes in relative wages. Lastly, we replace the qualification wage-bill shares with occupation employment shares to see if similar patterns emerge.

Our analysis comes with a number of caveats. First, our analysis is descriptive so any relationships should not be interpreted as causal. Second, we are looking at the impact of technology change among incumbent firms. Small firms or firms new to the market are not included in the BOS population and these firms may be an important source of technological disruption. Our sample selection means that we are focussing on large firms so these may not be representative of the whole firm population. However, these firms account for a large fraction of employment so what happens in these firms does matter for aggregate outcomes. We are also looking at impacts on firms that report a technology change. One firm adopting a new technology may give them a competitive advantage and therefore any negative effects may be felt in competing firms as they potentially lose market share. Finally, the nature of our technology change question is very general – we don't know what technologies firms are adopting or the capabilities of the new technologies. Our results will give us a sense of the general nature of technology change over the period.

[25] The innovation module is run every second year whereas technology change question is asked every year. We assume that, if an organisational or process innovation occurred in the previous two years (as is asked in the innovation module), it occurred in both the year of the innovation module and in the previous year.
[26] Technology change and innovation may in some cases be the same thing. For instance, the purchase of a new computer network may be a technology change but also a process change. While there is significant overlap between firms that report major technology changes and those that report organisational or process innovation, the overlap is not complete. This suggests in most cases they are representing different changes.

5 Results

5.1 Correlates of technology change

We now turn to the results of our model looking at the firm characteristics that are associated with different answers to the technology change question. Table 2 shows the marginal effects from an ordered logit model looking at the firm-level characteristics that predict the degree of technology change reported. Column 1 shows the results for no technology change, column 2 the results for minor technology change, and column 3 the results for major technology change.

In general, the factors that significantly predict major technology change are also associated with minor technology change. Here we see further evidence that large firms are more likely to report some degree technology change. Firms with 1% higher value added are 8.5 percentage points more likely to report minor change and 2 percentage points more likely to report major technology change. These effects are large, taking into account the average for each category of 62.5% and 7.5%. Firms with more capital are also more likely to report some degree of technology change, although the size of this effect is much smaller than that for value added. After controlling for value added and capital, firms with lower employment are more likely to report change, consistent with more capital-intensive firms (higher K/L ratio) being more likely to report technology change.

The coefficients on exporting have the expected sign (exporters more likely to report a major technology change) but the coefficients are insignificant. Interestingly, foreign owned firms are less likely to report technology change.[27] Firms that report some form of innovation or doing R&D are more likely to report major technology change. There is some weak evidence that lower levels of competition are associated with a lower propensity to report major technology change, with firms reporting they operate in a captive market 0.7pp less likely to report major technology change than firms reporting they operate in a market with many competitors, none dominant. Although the empirical relationship is not strong, this is consistent with the qualitative findings of Pells & Howard (2019). Firms with older equipment are less likely to report major technology changes than firms with fully up-to-date technology, and this effect increases with the age of the equipment. That is, the results are suggestive that firms fall into groups, or exist in technological fields, with varying rates of technology change, rather than there being a common cycle of periodic upgrades, in which firms fall behind the frontier over time until they reach a point where updating is required.

Firms that report moderate or severe difficulty in hiring technicians, tradespeople, and other occupations are more likely to report a major technology change. This size of the effect is relatively large, at 0.4-0.5 percentage points, compared to an average of 7.5%. This suggests that difficulty in finding the required labour may be an important driver of the decision to make significant changes to production technology.

Firms with a larger share of the wage-bill going to workers with higher qualifications are more likely to report major technology change relative to firms with a larger share of

[27] Foreign ownership is correlated with size, so part of the coefficients on the size measures may be capturing the effect of foreign ownership.

the workforce with no qualifications. The size of the effect is increasing in the level of qualification up to a bachelor's degree. There is some evidence that firms that are already upskilling are more likely to report major technology change, as those with increasing share of the wage-bill going to workers with high-school or post-school qualifications are less likely, and those with an increasing share of bachelor's degrees are more likely to report major technology change.

Table 2: Marginal effects from ordered logit model predicting different levels of technology change

	$\Delta\text{Tech} = \text{none}$	$\Delta\text{Tech} = \text{minor}$	$\Delta\text{Tech} = \text{major}$
Firm age	-0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Ln Value added	-0.105***	0.085***	0.020***
	[0.019]	[0.017]	[0.005]
Ln K	-0.023***	0.019***	0.004***
	[0.004]	[0.004]	[0.001]
Ln RME	0.077***	-0.062***	-0.015***
	[0.017]	[0.015]	[0.004]
Ln VApw	0.091***	-0.074***	-0.017***
	[0.019]	[0.018]	[0.005]
Exporter	-0.013	0.011	0.002
	[0.009]	[0.008]	[0.001]
Foreign owned	0.049***	-0.038***	-0.011***
	[0.010]	[0.009]	[0.003]
Innovator	-0.187***	0.163***	0.024***
	[0.008]	[0.011]	[0.005]
Does R&D	-0.096***	0.0815***	0.015***
	[0.011]	[0.011]	[0.003]
Captive market	0.032	-0.025	-0.007*
	[0.020]	[0.016]	[0.004]
One or two competitors	-0.003	0.002	0.001
	[0.010]	[0.008]	[0.002]
Many competitors, several	-0.013	0.010	0.002
dominant	[0.008]	[0.006]	[0.002]
Core equipment < 4 years	-0.002	0.001	0.001
behind	[0.007]	[0.006]	[0.001]
Core equipment 4-10 years	0.034***	-0.026**	-0.007***
behind	[0.012]	[0.010]	[0.002]
Core equipment > 10 years	0.093***	-0.069***	-0.024***
behind	[0.022]	[0.020]	[0.005]
Difficulty hiring	-0.008	0.007	0.002
professionals/managers	[0.007]	[0.006]	[0.001]
Difficulty hiring technicians	-0.031***	0.025***	0.005***
	[0.008]	[0.007]	[0.002]
Difficulty hiring	-0.022***	0.018***	0.004***
tradespeople	[0.007]	[0.006]	[0.00149]
Difficulty hiring other	-0.022***	0.018***	0.004***
occupations	[0.006]	[0.006]	[0.001]
% high-school	-0.251***	0.203***	0.048***
	[0.044]	[0.041]	[0.012]
% post-school	-0.268***	0.217***	0.0514***
	[0.041]	[0.040]	[0.012]

% bachelor's	-0.331***	0.268***	0.064***
	[0.048]	[0.048]	[0.015]
% honours or above	-0.214***	0.173***	0.041***
	[0.054]	[0.048]	[0.013]
% missing quals	-0.160***	0.129***	0.031***
	[0.053]	[0.045]	[0.012]
Δ% high-school	0.135*	-0.109*	-0.026*
	[0.071]	[0.059]	[0.014]
Δ% post-school	0.148**	-0.120*	-0.028*
	[0.074]	[0.061]	[0.015]
Δ% bachelor's	0.131	-0.106	-0.025
	[0.088]	[0.072]	[0.017]
Δ% honours or above	0.002	-0.002	-0.000
	[0.105]	[0.085]	[0.020]
Δ% missing quals	0.177**	-0.143**	-0.034**
	[0.084]	[0.070]	[0.017]
N	35,223	35,223	35,223
N Firms	8,061	8,061	8,061
Mean dep var	30%	62.5%	7.5%

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The number of observations and number of firms have been randomly rounded to base 3 for confidentiality purposes. Model includes a set of industry*year dummies. Standard errors are clustered at the firm level. Marginal effects are calculated at the mean for the continuous variables and as a discrete change from 0 to 1 for the binary variables

The results above provide an overview of the types of firms that are more likely to report major technology change. These firms are larger and more capital intensive, have a more highly qualified workforce, engage in innovative activities, and report some difficulty in hiring workers.

5.2 Employment impacts

5.2.1 Lagged model

We now look at the relationship between technology change and our overall employment outcomes using our lagged model. Table 3 shows the results from estimating equation 3 for our overall employment outcomes: rolling mean employment (RME), total wage-bill, average monthly earnings, and the within-firm standard deviation of monthly earnings. Panel A shows the results for our main estimation sample, panel B excludes firms that report multiple instances of technology change, and panels C and D estimate the model on sub-periods of the data, 2007-2011 (panel C) and 2012-2016 (panel D).

In panel A, we see a strong, significant relationship between major technology change and employment and wage-bill growth. Firms that undertake major technology change experience 2.9 percentage point faster growth in employment, and 3.2 percentage point faster wage-bill growth. They also experience faster employment and wage-bill growth in the year following a change, although this could partly reflect multiple or ongoing instances of technology change. We see no relationship between major technology change and growth in average monthly earnings or changes in the earnings distribution at the firm.

Table 3: Results for lagged model – overall employment outcomes

	1	2	3	4
	log RME	log total wage-bill	log avg. monthly earn	std dev log monthly earn
Panel A: Main estimation sample (n obs = 23,214, n firms = 5,526)				
Major tech (t)	2.902***	3.184***	0.244	-0.206
	[0.509]	[0.517]	[0.297]	[0.489]
Major tech(t-1)	1.123**	1.009**	0.038	-0.210
	[0.466]	[0.480]	[0.298]	[0.530]
Major tech (t-2)	-0.063	-0.470	-0.265	0.063
	[0.447]	[0.452]	[0.278]	[0.487]
Mean dep var	0.21	3.66	3.50	-0.69
R^2	0.201	0.225	0.037	0.024
Panel B: Main estimation sample – single changers only (n obs = 18,897, n firms = 4,674)				
Major tech (t)	3.547***	3.432***	-0.344	0.437
	[0.815]	[0.815]	[0.488]	[0.759]
Major tech(t-1)	0.750	0.733	0.119	-0.013
	[0.708]	[0.728]	[0.474]	[0.828]
Major tech (t-2)	-0.413	-0.339	-0.045	0.708
	[0.681]	[0.691]	[0.417]	[0.760]
Mean dep var	-0.13	3.33	3.50	-0.62
R^2	0.209	0.233	0.041	0.027
Panel C: Main estimation sample – 2007-2011 (n obs = 11,337, n firms = 3,939)				
Major tech (t)	2.807***	2.986***	0.022	-0.827
	[0.761]	[0.804]	[0.463]	[0.720]
Major tech(t-1)	0.584	0.322	0.008	0.426
	[0.671]	[0.701]	[0.427]	[0.779]
Major tech (t-2)	0.671	0.239	-0.410	-0.195
	[0.663]	[0.677]	[0.403]	[0.709]
Mean dep var	-1.18	2.75	3.92	-0.71
R^2	0.215	0.246	0.046	0.026
Panel D: Main estimation sample – 2012-2016 (n obs = 11,877, n firms = 3,876)				
Major tech (t)	2.901***	3.276***	0.446	0.356
	[0.637]	[0.621]	[0.391]	[0.668]
Major tech(t-1)	1.568**	1.578**	0.0381	-0.770
	[0.621]	[0.627]	[0.420]	[0.736]
Major tech (t-2)	-0.781	-1.158*	-0.106	0.353
	[0.633]	[0.638]	[0.378]	[0.677]
Mean dep var	1.53	4.52	3.11	-0.67
R^2	0.178	0.200	0.025	0.023

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The number of observations and number of firms have been randomly rounded to base 3 for confidentiality purposes. Model includes a set of industry*year dummies. Standard errors are clustered at the firm level. All variables have been multiplied by 100, so that a coefficient of 1 represents a 1 percentage point change.

Panel B restricts the sample to firms reporting one instance of major technology change. We again see a strong, positive relationship between technology change and employment and wage-bill growth. The coefficient is larger in the year of a change than that estimated in panel A, although the coefficient on lagged change is no longer statistically significant. Firms reporting multiple instances of major technology change appear to be driving the lagged result found in panel A. Based on these results, we conclude that a single instance of major technology change is associated with a permanent increase in firm size.

Panels C and D present results for two sub-periods, 2007-2011 and 2012-2016. The coefficients on major technology change in the employment or wage-bill growth equations in panel C are slightly lower than those in panel D, and slightly lower than those for the overall estimation sample (panel A). Coefficients on the first lag are not statistically significant in the pre-GFC period, while they are significant in the post-GFC period. This suggests that repeated technology change has a stronger relationship with employment and wage-bill growth in the post-GFC period. We find no statistically significant relationship between major technology change and changes in firm earnings distributions, consistent with the other results in Table 3.

We next look at the relationship between technology change and the qualification structure of firm workforces. Table 4 presents the results for qualification wage-bill shares. The main result here is that technology change does not appear to be affecting the qualifications wage-bill structure in a significant way. The coefficients in all panels are very small and generally statistically insignificant, although there are a couple of exceptions, particularly in panels C and D which look at differences in the effects in the 2007-2011 and 2012-2016 periods. In panel C, we see a statistically significant decrease in the wage-bill share of those with no qualifications in the year following a major technology change (Major tech t-1), although this seems to be reversed the following year where the estimate is positive, significant, and of a similar magnitude (Major tech t-2). We do see some evidence of upskilling two years following a change in the 2007-2011 period, with an increase in the share of the wage-bill going to workers with a bachelor’s degree and a decrease in the share going to workers with a high-school qualification. In panel D, we see a significant increase in the share of the wage-bill going to workers with an honours degree or above two years after a change, but no significant reductions in the wage-bill share for other types of workers.

Results suggest that technology changes have had slightly different effects on the qualifications structure of firm wage-bills in the 2007-2011 and 2012-2016 periods. However, the estimates are very small, between 0.2 and 0.5 percentage points in absolute value. To put this in context, the average total wage-bill in our main estimation sample is $8 million. A 0.3 percentage point change in the share of the wage-bill going to workers with a bachelor’s degree (the estimate from panel C) represents an increase of $24,000, roughly 0.5 workers at the average annual wage.[28] In aggregate, this represents an extra 1,700 workers with a Bachelor’s degree, out of the total sample employment of 300,000-350,000. This likely overstates the number of extra workers with a Bachelor’s degree as these workers likely earn above the average wage.

[28] Even these estimates are likely to overstate the impact for highly skilled workers, as those with higher qualifications are expected to earn above the average wage.

Table 4: Results for lagged model – qualification wage-bill shares

	1 No quals	2 High school quals	3 Post-school quals	4 Bachelor's	5 Honours or above	6 Missing quals
Panel A: Main estimation sample (n obs = 23,214, n firms = 5,526)						
Major tech (t)	0.017	-0.078	0.041	0.070	0.090	-0.140
	[0.09]	[0.156]	[0.138]	[0.116]	[0.077]	[0.110]
Major tech(t-1)	-0.010	-0.053	-0.140	0.130	0.045	0.117
	[0.091]	[0.155]	[0.138]	[0.110]	[0.074]	[0.112]
Major tech (t-2)	0.062	-0.220	0.005	0.010	0.050	0.005
	[0.087]	[0.149]	[0.139]	[0.105]	[0.073]	[0.106]
Mean dep var	-0.33	0.21	-0.01	0.14	0.06	-0.07
R2	0.025	0.024	0.028	0.023	0.020	0.056
Panel B: Main estimation sample – single changers only (n obs = 18,897, n firms = 4,674)						
Major tech (t)	-0.012	0.012	0.052	0.107	0.173	-0.332*
	[0.150]	[0.261]	[0.234]	[0.185]	[0.128]	[0.171]
Major tech(t-1)	-0.037	-0.153	-0.151	0.073	0.086	0.182
	[0.149]	[0.243]	[0.215]	[0.178]	[0.105]	[0.175]
Major tech (t-2)	0.067	-0.128	-0.154	0.191	-0.071	0.095
	[0.137]	[0.236]	[0.221]	[0.158]	[0.106]	[0.165]
Mean dep var	-0.34	0.26	-0.02	0.13	0.05	-0.06
R2	0.028	0.027	0.031	0.027	0.026	0.057
Panel C: Main estimation sample – 2007-2011 (n obs = 11,337, n firms = 3,939)						
Major tech (t)	0.054	-0.115	-0.050	0.070	0.118	-0.078
	[0.134]	[0.229]	[0.214]	[0.173]	[0.111]	[0.156]
Major tech(t-1)	-0.281**	0.156	-0.311	0.113	0.142	0.180
	[0.132]	[0.218]	[0.193]	[0.162]	[0.106]	[0.155]
Major tech (t-2)	0.257**	-0.477**	0.106	0.295**	-0.131	-0.050
	[0.128]	[0.222]	[0.202]	[0.146]	[0.098]	[0.151]
Mean dep var	-0.30	0.17	0.21	0.24	0.12	-0.44
R2	0.027	0.021	0.023	0.022	0.017	0.021
Panel D: Main estimation sample – 2012-2016 (n obs = 11,877, n firms = 3,876)						
Major tech (t)	-0.011	-0.058	0.109	0.077	0.079	-0.195
	[0.125]	[0.212]	[0.191]	[0.153]	[0.107]	[0.154]
Major tech(t-1)	0.082	-0.261	0.022	0.146	-0.052	0.064
	[0.129]	[0.218]	[0.197]	[0.145]	[0.108]	[0.160]
Major tech (t-2)	-0.133	0.018	-0.101	-0.090	0.238**	0.068
	[0.120]	[0.196]	[0.187]	[0.150]	[0.108]	[0.149]
Mean dep var	-0.37	0.25	-0.23	0.06	0.00	0.29
R2	0.024	0.027	0.028	0.024	0.023	0.074

Notes: See notes to Table 3.

One reason why we may not be seeing much evidence of skill shift in these models is that wage-bill shares may be relatively slow-moving (especially in large firms) and that short-run changes may be a noisy measure of the long-run change (especially in small firms). Looking over a longer time horizon will mean there is more meaningful variation in the qualifications structure. This is what we turn to in the next section, which looks at our cohort regression results.

5.2.2 Cohort regressions

Table 5 presents the results from estimating equation 4 for the overall employment outcomes. This specification uses a long-difference as the left-hand side variable and the variables of interest are the number of major technology changes reported during that time. This allows us to more directly test whether firms that report multiple instances of major technology change experience different outcomes than those that report one change. The omitted group are the firms that reported no major technology change over the period. Panel A shows the results for the combined 2006 and 2012 cohorts, panel B the results for the 2006 cohort, and panel C the results for the 2012 cohort.

The results in the first two columns of panel A confirm our previous finding – that major technology change has a strong relationship with employment and wage-bill growth. The coefficients on one major change are similar in magnitude to those in panel B of Table 3, which restricted attention to firms that reported only one instance of major technology change. The coefficients on two major changes are similar in magnitude to those on one major change, but statistically insignificant. It's possible that these firms have similar experiences to those reporting one major change, but given the relatively small number of firms reporting multiple instances we cannot estimate this effect with sufficient precision. The coefficients on three major changes, on the other hand, are very large and significant. While this group of firms is very small, their experience is significantly different from those reporting one or two major changes.

Some differences are apparent when examining panels B and C, which look at the 2006 (B) and 2012 (C) cohorts. For the 2006 cohort, the coefficients on one major change are larger than for the 2012 cohort and are statistically significant. Conversely, the coefficients on three major changes are larger in the 2012 cohort than the 2006 cohort and are statistically significant. This could be the result of more firms undertaking repeated technology change in the later cohort, aiding us in getting more precise estimates. It could also be that the types of technologies being adopted in the later cohort are somehow different, allowing firms to rapidly build upon a previous technology change with greater impacts on the firm. A final possibility is that the larger coefficients could reflect the better economic conditions facing the 2012 cohort. Firms that made a technology change in 2006 then faced the GFC two years later, potentially limiting the returns to investing in new technology and therefore limiting the labour market effects.

One difference between these results and those in Table 3 is that we see a significant impact on within-firm earnings dispersion. Firms that report one major change see an increase in the standard deviation of (log) average monthly earnings compared to firms that report no change, and also relative to firms that report multiple instances of major technology change. This result is most evident in the 2006 cohort and is not significant in the 2012 cohort. This may be consistent with the types of technologies being adopted differing between the 2006 and 2012 cohorts, with different impacts or workforce responses by firms. We still see no significant change in average monthly earnings at firms that report any number of major technology changes, which is somewhat puzzling given the change in the dispersion of monthly earnings.

Table 6 presents the results from estimating equation 4 for the wage-bill shares. Panel A shows the results for both cohorts combined, panel B the results for the 2006 cohort, and panel C for the 2012 cohort. In general, we see stronger evidence of shifts in the skill distribution in this specification than in the lagged model.

Table 5: Results for long-difference cohort regressions - overall employment outcomes

	1 log RME	2 log total wages	3 log avg. monthly earn	4 std dev log monthly earn
Panel A: Combined 2006 and 2012 cohorts (n obs = 4,458 n firms 3,591)				
1 Major change	3.153**	2.825**	-0.741	1.908*
	[1.412]	[1.403]	[0.743]	[1.031]
2 Major changes	2.782	3.646	0.941	-1.698
	[2.480]	[2.457]	[1.139]	[1.529]
3 Major changes	16.12***	14.71***	-0.487	-1.876
	[5.295]	[5.078]	[2.112]	[3.048]
Mean dep var	8.64	19.70	10.74	-1.06
R^2	0.351	0.388	0.061	0.026
Panel B: 2006 cohort (n firms/obs = 2,058)				
1 Major change	3.876**	3.121*	-1.291	2.787*
	[1.891]	[1.868]	[1.059]	[1.486]
2 Major changes	1.376	2.531	0.846	-2.568
	[3.507]	[3.395]	[1.732]	[2.335]
3 Major changes	13.96	12.39	-0.599	1.168
	[9.057]	[8.561]	[2.861]	[4.208]
Mean dep var	7.92	21.92	13.58	-1.87
R^2	0.326	0.364	0.031	0.031
Panel C: 2012 cohort (n firms/obs = 2,400)				
1 Major change	2.724	2.792	-0.260	1.032
	[2.044]	[2.034]	[1.055]	[1.467]
2 Major changes	4.039	4.746	1.083	-1.051
	[3.440]	[3.462]	[1.503]	[1.999]
3 Major changes	18.21***	16.92***	-0.396	-4.009
	[6.082]	[5.922]	[3.005]	[4.235]
Mean dep var	9.26	17.79	8.30	-0.37
R^2	0.379	0.412	0.032	0.022

Notes: See notes to Table 3.

In panel A, we see positive and significant increases in the share of the wage-bill going to those with an honours degree or above for firms reporting at least one instance of major technology change, with the size of the estimate increasing in the number of changes. Firms that report one instance of major technology change also see an increase in the share of the wage-bill going to workers with a bachelor's degree. Firms that report three instances of major technology change experience an increase in the share of the wage-bill going to workers with an honours degree or above of two percentage points, offset by a reduction in the share of the wage-bill going to workers with post-school qualifications. This represents a change in the wage-bill for workers with an honours degree or above of $160,000, equivalent to nearly three extra workers at the average annual salary (though fewer at the average salary of workers with post-graduate qualifications). However, given the small number of firms that report undertaking three major technology changes, this implies an aggregate increase in the number of workers with an honours degree or above of less than 50.

We see similar patterns in panels B and C, with increases in the share of the wage-bill going to workers with an honours degree or above. Firms in the 2006 cohort that report one instance of major technology change also experience an increase in the share of the wage-bill going to those with a bachelor's degree, as do firms in the 2012 cohort that report three instances of major technology change. We do not see any negative and significant coefficients as we do in panel A, although the coefficients on three major changes for post-school qualifications and no qualifications are relatively large in magnitude, but imprecisely estimated. As with the estimates from Table 4, the coefficients for the 2012 cohort are generally larger than those for the 2006 cohort.

The most consistent finding in our main results is that technology change is associated with a permanent increase in employment. We found this in both our lagged specification and our long-difference specification. We also see that firms that report multiple instances of technology change experience larger impacts than firms that report one instance of major technology change. There is suggestive evidence of this in our lagged specification but is more clearly seen in our long-difference specification. We see little evidence of changes to the skill distribution of firm workforces in our lagged model, possibly because there is relatively little year-to-year variation in the wage-bill shares. In our long-difference specification, we see some evidence of upskilling, with the share of the wage-bill going to workers with an honours degree or above increasing. There is suggestive evidence of hollowing out, with the share of the wage-bill going to workers with post-school qualifications decreasing in the specification that included both the 2006 and 2012 cohorts. While statistically significant, the estimated changes in qualifications composition are not large. Given the results for the changes in workforce composition and employment growth, we conclude that the changes in workforce composition arise from firms hiring more highly qualified workers, rather than changes in the returns to skill or qualifications.

The other main finding is the difference in coefficients in the two sub-periods. In both models, the coefficients for the later period (2012-2016 and the 2012 cohort in the long-difference model) are larger. This suggests that the relationship between technology change and changes in the labour market are increasing over time, although the estimated coefficients are still small.

Table 6: Results for long-difference cohort regressions - qualification wage-bill shares

	1	2	3	4	5	6
	No quals	High school quals	Post-school quals	Bachelor's	Honours or above	Missing quals
Panel A: Combined 2006 and 2012 cohorts (n obs = 4,458 n firms 3,591)						
1 Major change	-0.156	-0.186	-0.382	0.551*	0.578***	-0.405
	[0.260]	[0.465]	[0.391]	[0.319]	[0.221]	[0.296]
2 Major changes	-0.264	-1.036	-0.364	0.498	0.803*	0.362
	[0.399]	[0.747]	[0.628]	[0.468]	[0.460]	[0.576]
3 Major changes	-1.231	0.330	-1.959*	1.028	2.029***	-0.197
	[0.974]	[1.386]	[1.147]	[0.735]	[0.663]	[1.009]
Mean dep var	-1.19	0.97	0.13	0.75	0.35	-1.01
R2	0.044	0.043	0.032	0.030	0.029	0.036
Panel B: 2006 cohort (n firms/obs = 2,058)						
1 Major change	-0.604	-0.189	-0.333	0.810*	0.621*	-0.305
	[0.378]	[0.702]	[0.507]	[0.470]	[0.326]	[0.446]
2 Major changes	-0.124	-0.727	-0.196	0.403	0.113	0.532
	[0.684]	[1.109]	[0.909]	[0.722]	[0.670]	[0.926]
3 Major changes	0.191	1.339	-3.038	-0.476	1.744*	0.241
	[0.876]	[2.275]	[2.045]	[1.292]	[1.023]	[1.289]
Mean dep var	-1.20	0.40	0.44	1.09	0.41	-1.13
R2	0.053	0.032	0.036	0.019	0.035	0.034
Panel C: 2012 cohort (n firms/obs = 2,400)						
1 Major change	0.253	-0.165	-0.416	0.282	0.537*	-0.491
	[0.364]	[0.639]	[0.603]	[0.425]	[0.304]	[0.388]
2 Major changes	-0.379	-1.311	-0.523	0.571	1.426**	0.215
	[0.471]	[1.033]	[0.878]	[0.656]	[0.609]	[0.710]
3 Major changes	-2.289	-0.347	-1.173	2.081**	2.265**	-0.538
	[1.548]	[1.738]	[1.278]	[0.893]	[0.885]	[1.479]
Mean dep var	-1.18	1.46	-0.14	0.45	0.31	-0.90
R2	0.039	0.049	0.027	0.040	0.029	0.039

Notes: See notes to Table 3.

5.2.3 Technology change and innovation

We next look at the interaction between technology change and organisational or process innovations. Other studies find a complementarity between technology and organisational changes (e.g. Piva et al. 2005), so we expect the coefficients to be larger on the interaction terms.

Table 7 reports the results from estimating equations 3 and 4 with the dummy variables for technology change only, organisational or process innovation only, and technology change with organisational or process innovation. The results in Panel A for undertaking major technology change only are similar to our baseline results in Table 3. We see strong growth in both employment and wage-bills in the year of the change, but we see no significant relationships between major technology change and changes in the firm earnings distribution. We see no significant relationship between firm employment or the earnings distribution for firms that undertake organisational or process innovations only.

We do see a strong relationship between major technology change alongside organisational or process innovations and employment and wage-bill growth. The coefficients are larger than those on major technology change only, suggesting a complementarity between major technology and organisational or process innovations.

Panel B shows the results from the long-difference model. Firms that report undertaking one major technology change over a three year period experience more rapid employment growth. This result holds whether or not there was an organisational or process innovation undertaken over the same period. We do see some evidence of a widening of the firm earnings distribution for firms reporting one major technology change only, which is consistent with our baseline results. We see no significant relationships between employment or wage-bills among firms that report two major technology changes. Interestingly, firms that report a major technology change only do experience an increase in wage dispersion within the firm, whereas firms that also report an organisational or process innovation do not. The coefficients on three major technology changes only in the employment and wage-bill equations are large and similar to our baseline estimates, but statistically insignificant. We do see a substantial widening of the firm earnings distribution for these firms. Firms that undertake an organisational or process innovation only (i.e. no major technology change) experienced greater employment and wage-bill growth, although the magnitude of the coefficients are generally smaller than those on major technology change only. Again, these results are consistent with a complementarity between technology change and organisational change.

Table 8 shows the results for qualification wage-bill shares, with panel A showing the lagged model and Panel B showing the cohort model. As with the baseline model (Table 4), we see little evidence of a relationship between technology change and changes in the skill composition of the workforce in the lagged model (panel A). The strongest results are for firms that undertake an organisational or process innovation only. In the year the innovation was introduced, we see a small shift away from workers with no qualifications towards workers with a post-school qualification.

Table 7: Relationship between technology change, organisational/process innovations and overall employment outcomes

	1 log RME	2 log total wage-bill	3 log avg. monthly earn	4 std dev log monthly earn
Panel A: Lagged model - main estimation sample (n obs = 23,214, n firms = 5,526)				
Major tech only (t)	2.679***	2.783***	-0.0670	-0.028
	[0.665]	[0.679]	[0.399]	[0.615]
Major tech only (t-1)	1.033	1.012	0.506	-0.762
	[0.666]	[0.700]	[0.461]	[0.754]
Major tech only (t-2)	0.604	0.0729	-0.445	1.118
	[0.712]	[0.692]	[0.392]	[0.714]
Org or process innovation only (t)	0.0962	0.328	0.171	-0.060
	[0.305]	[0.320]	[0.213]	[0.338]
Org or process innovation only (t-1)	0.351	0.427	-0.056	0.511
	[0.373]	[0.381]	[0.241]	[0.426]
Org or process innovation only (t-2)	-0.514	-0.482	0.142	-0.279
	[0.317]	[0.317]	[0.184]	[0.334]
Major tech and org/process innovation (t)	3.041***	3.534***	0.637	-0.655
	[0.632]	[0.647]	[0.404]	[0.691]
Major tech and org/process innovation (t-1)	1.609***	1.408**	-0.382	0.619
	[0.606]	[0.631]	[0.395]	[0.728]
Major tech and org/process innovation (t-2)	-0.773	-1.158**	-0.101	-0.756
	[0.547]	[0.557]	[0.348]	[0.601]
Mean dep var	0.21	3.66	3.50	-0.69
R2	0.201	0.225	0.037	0.024
Panel B: Long-difference model - combined 2006 and 2012 cohorts (n obs = 4,458 n firms 3,591)				
1 Major tech only	4.366*	3.199	-1.144	3.111**
	[2.252]	[2.225]	[1.072]	[1.501]
1 Major tech and org/process innovation	4.538**	4.072**	-0.711	2.270
	[1.954]	[1.962]	[1.055]	[1.412]
2 Major tech only	0.701	-0.204	-2.333	2.225
	[4.806]	[4.379]	[2.379]	[3.558]
2 Major tech and org/process innovation	1.090	2.471	1.900	-3.305*
	[2.756]	[2.741]	[1.321]	[1.752]
3 Major tech only	14.44	13.68	-1.442	14.00***
	[17.31]	[14.95]	[5.027]	[4.469]
3 Major tech and org/process innovation	16.69***	15.14***	-0.331	-4.070
	[5.439]	[5.327]	[2.268]	[3.237]
Org/process innovation only	2.045**	2.204**	0.146	1.070
	[1.009]	[0.992]	[0.497]	[0.778]
Mean dep var	8.64	19.70	10.74	-1.06
R2	0.351	0.388	0.061	0.028

Notes: see notes to Table 3.

Table 8: Relationship between major technology change, organisational/process innovation and qualifications structure

	1 No quals	2 High school quals	3 Post-school quals	4 Bachelor's	5 Honours or above	6 Missing quals
Panel A: Lagged model - main estimation sample (n obs = 23,214, n firms = 5,526)						
	0.018	-0.133	0.110	0.101	0.011	-0.108
Major tech only (t)	[0.135]	[0.207]	[0.193]	[0.150]	[0.108]	[0.154]
	-0.036	-0.217	-0.086	0.103	-0.065	0.300*
Major tech only (t-1)	[0.128]	[0.229]	[0.210]	[0.171]	[0.114]	[0.163]
	0.092	-0.336	0.098	0.058	0.067	0.022
Major tech only (t-2)	[0.138]	[0.209]	[0.214]	[0.175]	[0.122]	[0.169]
Org or process innovation	-0.141**	-0.050	0.179*	0.101	0.029	-0.119
only (t)	[0.0632]	[0.104]	[0.0928]	[0.0715]	[0.053]	[0.075]
Org or process innovation	0.064	-0.033	-0.137	-0.018	-0.017	0.141
only (t-1)	[0.074]	[0.123]	[0.117]	[0.087]	[0.060]	[0.088]
Org or process innovation	-0.076	0.010	0.093	-0.037	0.075	-0.065
only (t-2)	[0.060]	[0.099]	[0.092]	[0.070]	[0.047]	[0.070]
Major tech and org/process	-0.053	-0.056	0.117	0.099	0.150	-0.256*
innovation (t)	[0.113]	[0.206]	[0.179]	[0.162]	[0.102]	[0.142]
Major tech and org/process	-0.041	0.013	-0.305*	0.131	0.058	0.143
innovation (t-1)	[0.121]	[0.206]	[0.183]	[0.147]	[0.101]	[0.149]
Major tech and org/process	0.023	-0.146	0.006	0.084	0.072	-0.039
innovation (t)	[0.103]	[0.190]	[0.168]	[0.128]	[0.089]	[0.129]
R2	0.025	0.024	0.028	0.023	0.020	0.056
Mean dep var	-0.33	0.21	-0.01	0.14	0.06	-0.07
Panel B: Long-difference model - combined 2006 and 2012 cohorts (n obs = 4,458 n firms 3,591)						
	0.179	-0.303	-1.396**	0.781	0.680**	0.058
1 Major tech only	[0.384]	[0.750]	[0.681]	[0.537]	[0.336]	[0.451]
1 Major tech and	-0.054	-0.944	-0.420	0.702	0.961***	-0.245
org/process innovation	[0.309]	[0.623]	[0.444]	[0.447]	[0.356]	[0.453]
	0.671	-0.001	-1.460	1.209	0.508	-0.927
2 Major tech only	[0.754]	[1.662]	[1.207]	[1.077]	[0.725]	[1.347]
2 Major tech and	-0.319	-0.834	-0.0434	0.0292	0.405	0.761
org/process innovation	[0.458]	[0.838]	[0.679]	[0.534]	[0.532]	[0.659]
	-0.298	3.807	-4.919*	0.504	2.659	-1.752
3 Major tech only	[0.887]	[2.362]	[2.866]	[1.400]	[1.828]	[2.964]
3 Major tech and	-1.325	-0.290	-1.586	1.133	1.989***	0.0794
org/process innovation	[1.089]	[1.510]	[1.207]	[0.800]	[0.700]	[1.051]
	0.045	-0.414	-0.090	0.149	0.369***	-0.059
Org/process innovation only	[0.195]	[0.312]	[0.266]	[0.202]	[0.140]	[0.220]
Mean dep var	-1.19	0.97	0.13	0.75	0.35	-1.01
R2	0.045	0.044	0.033	0.031	0.031	0.036

Notes: See notes to Table 3.

Panel B shows the results for the cohort model. We see that firms that report undertaking one major technology change only (i.e. no other innovations) see a shift in their workforces away from individuals with post-school qualifications towards those with an honours degree or above. Firms that undertake one major technology change alongside an organisational or process innovation see a stronger shift towards workers with an honours degree or above. Firms that undertake three major technology changes only see a significant reduction in the share of the wage-bill going to workers with post-school qualifications, a reduction of nearly five percentage points. These firms see large increases in the share of the wage-bill going to workers with a high-school qualification or an honours degree or above, although these estimates are not statistically significant. Firms implementing an organisational or process innovation alongside three major technology changes see an increase in the share of the wage-bill going to workers with an honours degree or above and decreases going to those with post-school or no qualifications, although the reductions are not statistically significant.

The most consistent finding is that major technology change is associated with a permanent increase in firm size and the size of the effect is increasing in the number of technology changes reported over a three year period. We do find some evidence of small shifts in the qualification composition of employees, with firms that report a major technology change seeing an increase in the share of the wage bill going to workers with university qualifications. These effects are also increasing in the number of technology changes reported and are larger among firms that also report undertaking an organisational or process innovation.

5.3 Robustness checks

We also ran a number of robustness checks to check the consistency of our results (Tables B1 to B4 in Appendix B). First, we restrict our estimation sample further to include firms with a continuous five-year spell in the BOS sample. Second, we replace the qualifications wage-bill share variables with qualifications employment share variables to test our interpretation that we are seeing changes in the quantity of different types of labour rather than changes in the returns to different types of labour. Lastly, we used firm-reported occupation employment shares as the LHS variables. Occupation is the measure typically used to describe the skill structure of the workforce in international studies. All of the regressions are done using the technology change/organisational or process innovation interaction specification.

Table B1 (overall employment outcomes) and B2 (qualifications wage-bill shares) show the results from estimating our lagged model on a subsample of firms that have a spell in the BOS sample of at least five continuous years. The main difference between the results in Table B1 and our main results in Table 3 are differences in the time profile of the relationship between technology change and employment growth. In our main results, the contemporaneous relationship between technology change and employment was the strongest; in B1 the relationship is strongest on the first lag. The results for total wage-bill are similar to those in Table 3. We still see no relationship between technology change and changes in the firm earnings distribution. In Table B2, we see little evidence of a relationship between major technology change and changes in the qualifications distribution, consistent with our results in Table 4.

Panel A of Table B3 shows the results from estimating our lagged model using qualifications employment shares as opposed to wage-bill shares as our left-hand side variable. Again, we see little evidence of a relationship between technology change and changes in the qualifications distribution when this is measured as employment shares. Panel B shows the results from our cohort model. The results are consistent when using employment shares and the coefficients are generally of a similar magnitude. In some cases, the coefficients on employment shares are slightly smaller, pointing to some groups of workers possibly experiencing small wage premiums following a major technology change. This is consistent with the results of Fabling & Grimes (2019) for UFB.

Table B4 presents the results from using occupation employment shares as reported in BOS as the LHS variable. Panel A presents results from the lagged model, while panel B shows the results from the cohort model. It is difficult to interpret the occupation results in the context of a task-based model of technology change. We would expect to see firms increase the share of professionals and technicians and this is not what we find in general. Some groups of firms that report major technology change do see reductions in the share of other occupations, but this is not a general pattern that we see. This could be due to the range of occupations that are included in the other category, which are a mixture of medium and low-skilled occupations. Variation in the composition of this category across firms, or over time within firms, could make it difficult to establish a clear link with technology change.

6 Conclusions and discussion

We test whether major technology changes impact the types of labour that firms hire. We use an event-study type approach to look at whether firms reporting major technology change have different growth experiences following a change, whether there are changes in the within-firm earnings distribution, and whether they change their skill demands. We use the qualifications structure of firm workforces to measure skill demands.

We find that large firms, those with more skilled workforces, those that undertake R&D and other innovative activities, and those that report hiring difficulties are more likely to report a major technology change.

Overall, the results suggest that technology change has not had a major impact on the New Zealand labour market over the period 2005-2016. The main effect we find is a permanent increase firm size. There is no clear evidence of a large shift in either the average level of wages, or the width of the firm earnings distribution.

We do find some evidence of shifts in the qualifications wage-bill share in our cohort models, with the share of the wage-bill going to workers with university-level qualifications increasing, with some weaker evidence suggesting this is at the expense of workers with post-school qualifications. This is particularly true for the small group of firms that report three major technology changes over a three year period. However, the sizes of the effects are relatively small, equivalent to between 0.5 and 3 extra workers at the average wage for an "average" firm. The effects are more concentrated in the subset of firms that undertake an organisational or process innovation alongside the major technology changes, consistent with a complementarity between technological and organisational changes.

The within-firm results are broadly consistent with a task-based model of technology change. Workers with higher-level qualifications appear to benefit from a major technology change. The evidence for one group being disproportionately negatively impacted is less robust, but suggests those with post-school but pre-degree qualifications may be most affected. However, as noted above, our estimated effects are small.

The increase in the wage-bill, coupled with the strong employment growth and the finding that more skill-intensive firms are more likely to undertake major technology change, does point to a role of technology change in the reallocation of labour across firms. Firms that are already larger and more skill intensive become larger following a major technology change and continue to upskill their workforces.

Our results are consistent with the findings of the recent Productivity Commission inquiry into technology change and the future of work. They find that New Zealand hasn't experienced major technology related disruptions and is unlikely to in the immediate future. However, our results for the firms that report three major technology changes are indicative of the types of effects we may see in the future, as technology advances and adoption becomes more widespread. Our sub-period results also suggest that the relationship between technology change and changes in the labour market is getting stronger. However, we do not see an increasing trend in the proportion of firms reporting a major technology change. Any effects are likely to become more apparent when this proportion increases. Monitoring the proportion of firms that report undertaking major technology change, and those reporting repeated instances of technology change, will be important for signalling when more substantial labour market impacts may be on the horizon.

Both our work and that of the Productivity Commission is based on pre-COVID data. Some firms may have accelerated their uptake of technology in response to COVID-related restrictions on trading. The extent to which this technology uptake represents novel new technologies is not clear. In a period of high uncertainty firms are likely to have delayed risky investments in new and novel technologies. Some of the technologies adopted may already be widely available and used (e.g. online sales). McKinsey (2020) provides some evidence that firms have adopted automation and artificial intelligence to help them cope with the disruption. Results from the 2020 BOS survey will give some indication into the impact of COVID on the uptake of new technologies and further work can examine the impact of COVID on firm and labour market dynamics and the role of technology change in these.

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Appendix A: Correlation of firm-level behaviours and technolgy change

While we cannot directly observe the type of technology change firms are undertaking, we can get some clues by examining the relationship between technology change and investment in different types of physical capital. By combining our BOS data with information from AES, we can directly test whether firms that report some level of technology change are actually investing in more physical capital, and if so, in what broad asset types.[29]

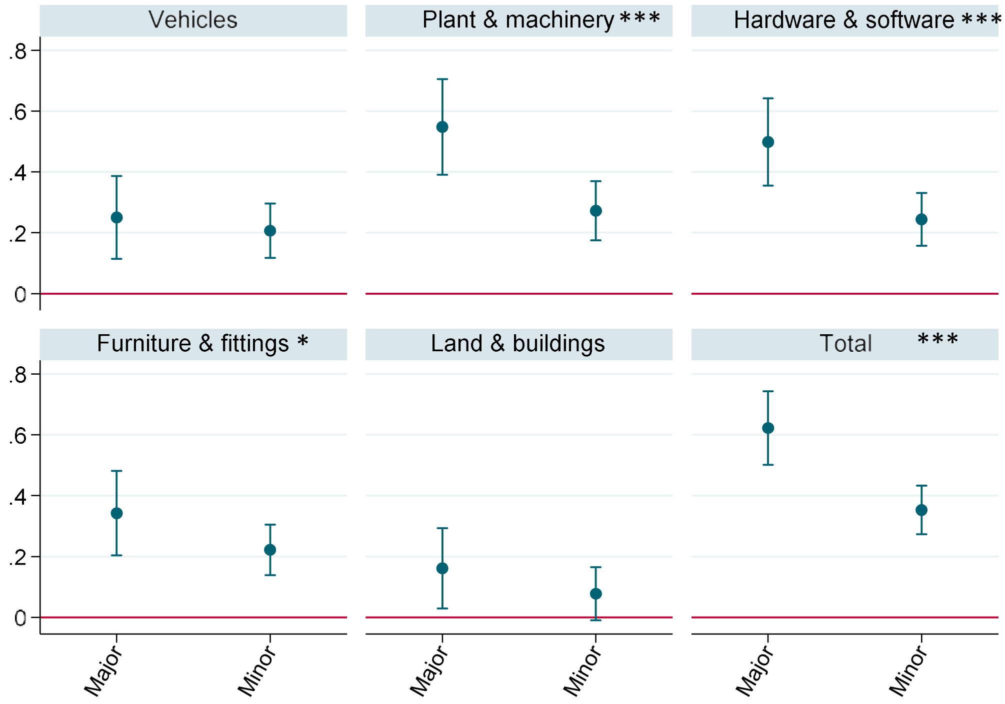
We take information on total capital additions, and on additions in the five asset classes recorded in AES, and regress the natural log of additions per worker on dummy variables for major and minor technology change, a firm fixed effect, and industry*year dummies.[30] This specification uses within-firm variation and tests whether investment is higher in years that firms report some degree of technology change compared to years where they report no change. We also test whether years of major technology change are associated with higher levels of investment than years of minor technology change. We expect that new technologies would be embedded in new plant and machinery and computer hardware and software, so we expect a stronger relationship between technology change and investment in these categories.

Figure A1 plots the estimated coefficients on the major and minor technology change variables.[31] Positive answers to the technology change question are associated with significantly higher levels of investment relative to years where firms answer 'no change' for all asset classes. There is strong evidence that years of major technology change are associated with higher levels of investment in plant and machinery and computer hardware and software than years of minor technology change. The same is true for total investment. This gives us some confidence that answers to the technology change question do reflect changes to a firm's capital vintage.

[29] AES information is available for 42% of our BOS sample

[30] The asset classes are: vehicles; plant, machinery and equipment (and other); computer hardware and software; furniture and fittings; and land and buildings.

Figure A1: Relationship between level of technology change and investment per worker from firm fixed-effect model



Notes: *, **, and *** indicates the rejection of the null hypothesis that the coefficients on major and minor change are equal at the 10%, 5%, and 1% level of significance, respectively.

Another behaviour which has been examined alongside technology change is different forms of innovation, particularly organisational changes and process innovations (see Caroli & Van Reenen 2002; Piva et al. 2005, among others). The BOS innovation module gives us information on whether the firm has introduced a new good or service, a process innovation, an organisational/managerial innovation, or a marketing innovation in the previous two years (module B, in odd numbered years).

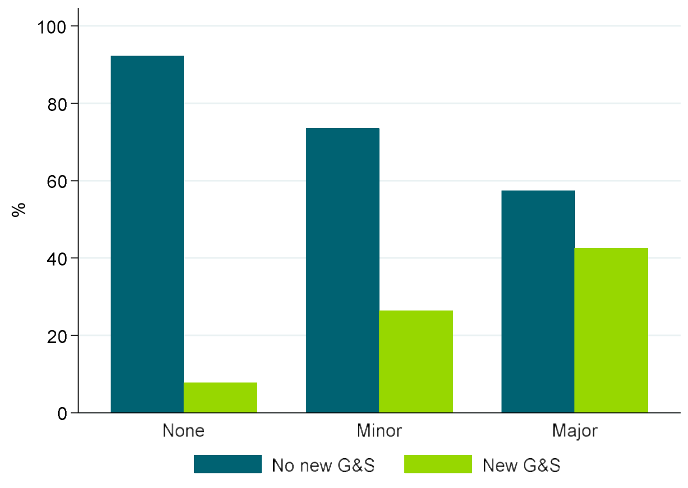
Figure A2 shows the relationship between technology change and different types of innovation.[32] Panel A shows the responses to introducing a new good or service, panel B a new operational process, panel C a new organisational process, and panel D new marketing methods. Whether or not a firm reports an innovation is positively correlated with the level of technology change they report for all types of innovation. Over 90% of firms that report no technology change also report no type of innovation. The most commonly reported types of innovation among firms that report major

[32] Questions on the types of innovation undertaken refer to the previous two financial years. We look at firms' responses to the technology change question in the year of the innovation module and the previous year. We categorise firms according to whether they did any major or minor technology change in the period covered by the innovation module, restricting to firms with both years of BOS.

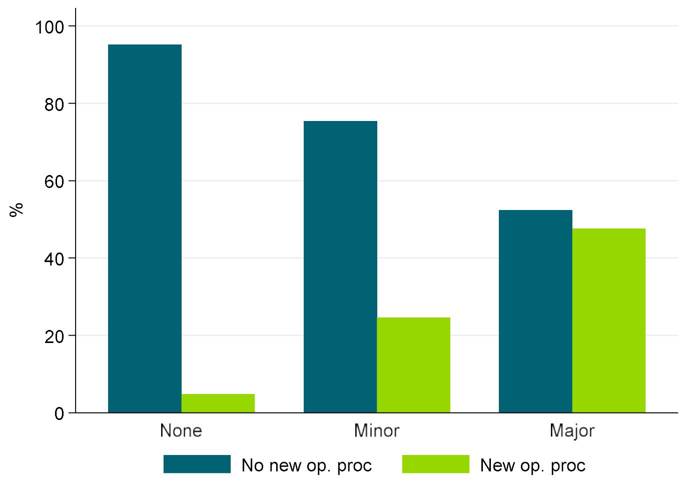
technology change are new operational and organisational processes (47% and 46%, respectively).

Figure A2: Frequency of different types of innovation occurring alongside different levels of technology change

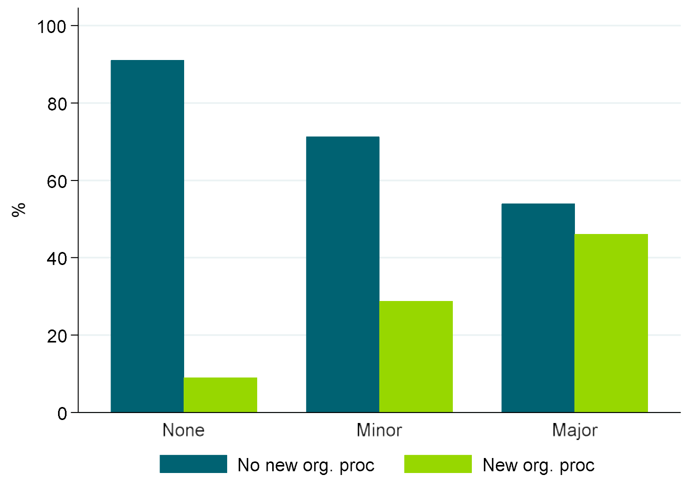
Panel A: New goods and services



Panel B: New operational processes



Panel C: New organisational/managerial processes



Panel D: New marketing methods

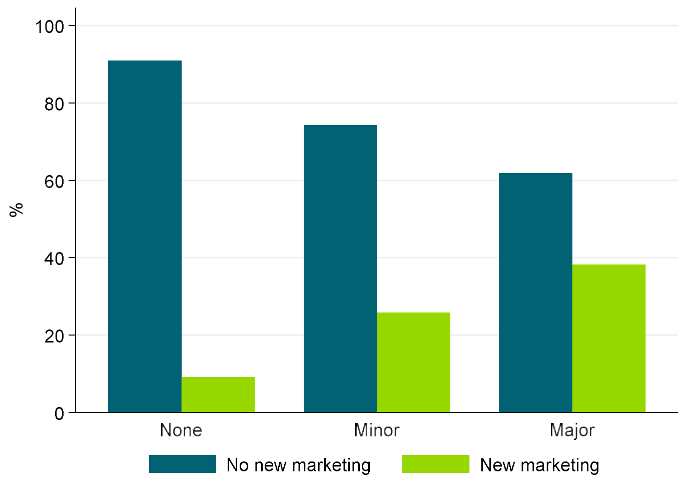
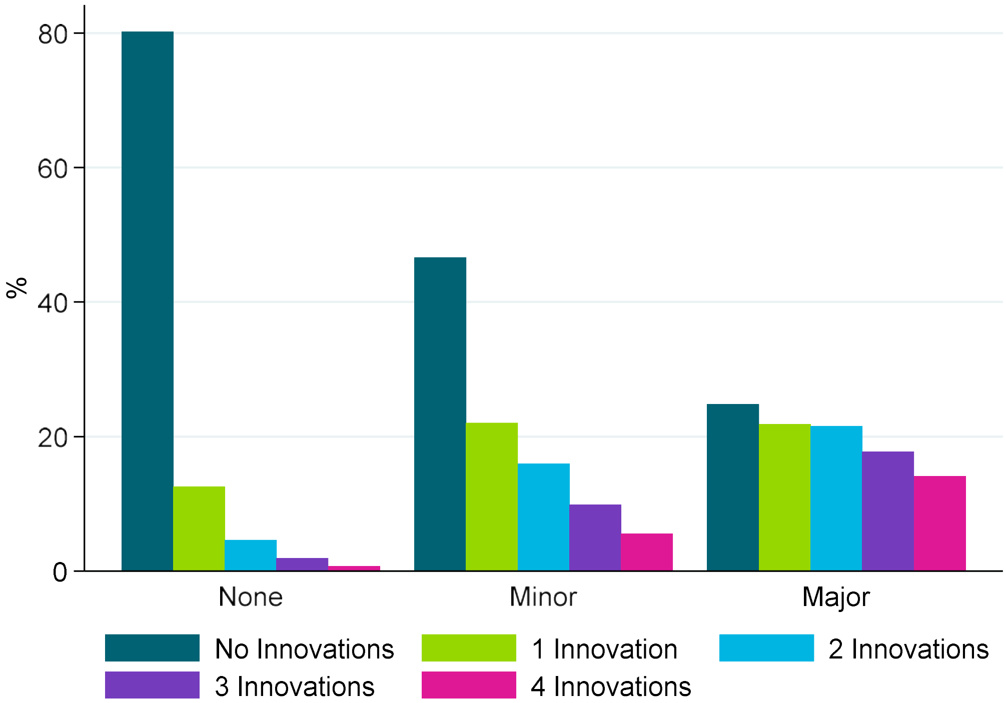


Figure A3 shows how often firms report multiple types of innovation at the same time by the extent of technology change. Of those who report undertaking major technology change, 53% report doing at least two types of innovation, while only 24% report undertaking no innovation.

Figure A3: Frequency of multiple types of innovation by extent of technology change



Appendix B: Robustness results

Table B1: Employment regressions 5-year spell sample

	1	2	3	4
	log RME	log Total wages	log avg. monthly earn	std dev log monthly earn
	1.034	1.437*	-0.0838	0.646
Major tech only (t)	[0.867]	[0.861]	[0.466]	[0.805]
	1.387*	1.465	0.381	-0.994
Major tech only (t-1)	[0.829]	[0.903]	[0.614]	[1.011]
	0.273	-0.0225	-0.422	0.660
Major tech only (t-2)	[0.941]	[0.899]	[0.542]	[0.965]
Org or process innovation	-0.212	-0.0264	0.264	0.264
only (t)	[0.391]	[0.410]	[0.260]	[0.436]
Org or process innovation	0.641	0.573	-0.246	0.274
only (t-1)	[0.446]	[0.458]	[0.300]	[0.540]
Org or process innovation	-0.482	-0.350	0.174	-0.676
only (t-2)	[0.367]	[0.368]	[0.235]	[0.428]
Major tech and org/process	2.009***	2.797***	0.466	0.124
innovation (t)	[0.748]	[0.770]	[0.535]	[0.941]
Major tech and org/process	2.652***	1.905**	-0.736	0.0337
innovation (t-1)	[0.823]	[0.832]	[0.498]	[0.936]
Major tech and org/process	-0.650	-0.816	0.229	-0.963
innovation (t-2)	[0.723]	[0.709]	[0.437]	[0.781]
R^2	0.212	0.238	0.043	0.033
Mean dep var	-0.112	2.87	3.08	-0.541
N	12,600	12,600	12,600	12,600
N Firms	3,327	3,327	3,327	3,327

Notes: See notes to Table 3.

Table B2: Qualifications wage-bill share regressions 5-year spell sample

	1 No quals	2 High school quals	3 Post-school quals	4 Bachelor's	5 Honours or above	6 Missing quals
Major tech only (t)	0.0859 [0.166]	-0.0703 [0.265]	0.0748 [0.235]	-0.00375 [0.206]	0.0463 [0.140]	-0.133 [0.177]
Major tech only (t-1)	0.151 [0.171]	0.0480 [0.276]	-0.0395 [0.266]	0.0639 [0.212]	-0.327** [0.147]	0.104 [0.200]
Major tech only (t-2)	-0.0421 [0.179]	-0.281 [0.260]	0.00971 [0.266]	0.134 [0.234]	0.177 [0.171]	0.00242 [0.188]
Org or process innovation only (t)	-0.102 [0.0806]	0.0221 [0.135]	0.111 [0.119]	0.137 [0.0946]	-0.00586 [0.0696]	-0.161* [0.0955]
Org or process innovation only (t-1)	0.0902 [0.0936]	-0.0194 [0.155]	-0.105 [0.147]	-0.118 [0.107]	-0.0253 [0.0814]	0.177 [0.116]
Org or process innovation only (t-2)	-0.0652 [0.0752]	0.0178 [0.121]	0.0313 [0.112]	0.0235 [0.0849]	-0.0268 [0.0599]	0.0194 [0.0917]
Major tech and org/process innovation (t)	0.0285 [0.142]	0.111 [0.265]	-0.195 [0.219]	0.138 [0.217]	0.244** [0.120]	-0.327* [0.183]
Major tech and org/process innovation (t-1)	0.00172 [0.154]	0.0114 [0.249]	-0.0101 [0.228]	0.158 [0.188]	0.0361 [0.125]	-0.197 [0.186]
Major tech and org/process innovation (t-2)	-0.0907 [0.126]	-0.192 [0.228]	-0.0469 [0.204]	0.237 [0.155]	0.0684 [0.122]	0.0239 [0.163]
R^2	0.039	0.035	0.039	0.028	0.026	0.072
Mean dep var	-0.319	0.231	-0.086	0.101	0.063	0.011
N	12,600	12,600	12,600	12,600	12,600	12,600
N Firms	3,327	3,327	3,327	3,327	3,327	3,327

Notes: See notes to Table 3.

Table B3: Qualification employment share regressions

	1 No quals	2 High school quals	3 Post-school quals	4 Bachelor's	5 Honours or above	6 Missing quals
Panel A: Lagged model, main estimation sample (N = 23,214, N Firms = 5,526)						
Major tech only (t)	-0.00665	-0.0615	0.179	0.0776	-0.0641	-0.124
	[0.134]	[0.208]	[0.195]	[0.147]	[0.101]	[0.149]
Major tech only (t-1)	-0.000696	-0.323	0.0464	0.0419	0.00672	0.229
	[0.134]	[0.230]	[0.207]	[0.162]	[0.0991]	[0.159]
Major tech only (t-2)	0.0192	-0.216	0.0476	0.0773	0.0985	-0.0264
	[0.146]	[0.209]	[0.215]	[0.165]	[0.112]	[0.163]
Org or process innovation only (t)	-0.156**	0.0401	0.215**	0.0362	0.0136	-0.149**
	[0.0665]	[0.105]	[0.0943]	[0.0683]	[0.0473]	[0.0723]
Org or process innovation only (t-1)	0.109	-0.121	-0.191	0.0271	0.0280	0.148*
	[0.0777]	[0.125]	[0.118]	[0.0838]	[0.0563]	[0.0876]
Org or process innovation only (t-2)	-0.115*	0.0440	0.0998	-0.0507	0.0658	-0.0436
	[0.0624]	[0.100]	[0.0937]	[0.0679]	[0.0437]	[0.0697]
Major tech and org/process innovation (t)	-0.0863	-0.0665	0.162	0.123	0.121	-0.254*
	[0.118]	[0.209]	[0.181]	[0.163]	[0.0932]	[0.135]
Major tech and org/process innovation (t-1)	0.00227	-0.189	-0.273	0.191	0.0710	0.198
	[0.128]	[0.211]	[0.182]	[0.145]	[0.0935]	[0.149]
Major tech and org/process innovation (t-2)	-0.0565	-0.106	0.114	-0.0176	0.0364	0.0293
	[0.110]	[0.193]	[0.173]	[0.127]	[0.0825]	[0.129]
R^2	0.026	0.024	0.029	0.023	0.020	0.058
Mean dep var	-0.348	0.309	-0.044	0.086	0.016	-0.019
Panel B: Cohort model, combined 2006 and 2012 cohorts (N = 4,458, N Firms = 3,591)						
1 Major tech only	-0.0510	-0.511	-0.759	0.574	0.541*	0.206
	[0.405]	[0.742]	[0.694]	[0.494]	[0.303]	[0.421]
1 Major tech and org/process innovation	0.107	-1.027*	-0.180	0.644	0.710***	-0.254
	[0.316]	[0.596]	[0.454]	[0.422]	[0.270]	[0.418]
2 Major tech only	0.339	0.688	-0.546	0.481	0.658	-1.620
	[0.735]	[1.552]	[1.102]	[0.947]	[0.623]	[1.322]
2 Major tech and org/process innovation	-0.510	-0.439	-0.246	-0.264	0.822**	0.635
	[0.466]	[0.844]	[0.696]	[0.556]	[0.394]	[0.574]
3 Major tech only	-0.325	3.210	-4.616	2.012*	0.834	-1.115
	[0.842]	[2.814]	[3.302]	[1.210]	[0.998]	[2.933]
3 Major tech and org/process innovation	-1.439	-0.377	-1.274	1.162	1.601**	0.326
	[1.194]	[1.490]	[1.141]	[0.866]	[0.689]	[0.933]
Org/process innovation only	-0.0450	-0.389	0.0452	0.124	0.300**	-0.0348
	[0.202]	[0.314]	[0.266]	[0.189]	[0.126]	[0.213]
R^2	0.039	0.049	0.035	0.032	0.031	0.035
Mean dep var	-1.23	1.33	-0.04	0.54	0.24	-0.83

Notes: See notes to Table 3.

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