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COVID-19, PRODUCTIVITY AND REALLOCATION: TIMELY EVIDENCE FROM THREE OECD COUNTRIES

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ABSTRACT/RESUME

COVID-19, Productivity and Reallocation: Timely evidence from three OECD countries

The longer run consequences of the pandemic will partly hinge on its impact on high productivity firms, and the ongoing process of labour reallocation from low to high productivity firms. While Schumpeter (1939) proposed that recessions can accelerate this process, the nature of the COVID-19 shock coupled with a policy response that prioritised preservation (over reallocation) raises questions about whether job reallocation remained productivity-enhancing. Using novel, near-real-time data for Australia, New Zealand and the United Kingdom, this paper shows that while labour turnover fell in response to the pandemic, job reallocation remained connected to firm productivity – that is, high productivity firms were more likely to expand and low productivity firms were more likely to contract. The pandemic coincided with a temporary strengthening of the reallocation-productivity link in Australia – but a weakening in New Zealand – which appears related to the design of job retention schemes. Finally, firms that intensively used Apps to manage their business were more resilient, even after controlling for productivity. Thus, while policy partly suppressed creative destruction, the nature of the shock – i.e. one where being online and able to operate remotely were key – favoured high productivity and tech-savvy firms, resulting in a reallocation of labour to such firms. The use of timely, novel data to investigate the allocative effects of the pandemic marks a significant advance, given that the seminal paper on productivity-enhancing reallocation during the Great Recession arrived some six years after Lehman Brothers collapsed.

JEL classification codes: E24, E32, J63, O4.

Keywords: COVID-19, productivity, reallocation, recessions.

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COVID-19, Productivité et réallocation : enseignements de données en temps quasi-réel provenant de trois pays de l'OCDE

Les conséquences à long terme de la pandémie dépendront en partie de son impact sur les entreprises à forte productivité et du processus de réallocation de la main-d'œuvre des entreprises à faible productivité vers les entreprises à productivité élevé. Alors que selon Schumpeter (1939) les récessions devraient accélérer ce processus, la nature du choc COVID-19 couplée à une réponse politique privilégiant la préservation sur la réallocation pose la question de la mesure avec laquelle la réallocation des emplois durant la crise a effectivement été associé à une amélioration de la productivité. À l'aide de nouvelles données en temps quasi-réel pour l'Australie, la Nouvelle-Zélande et le Royaume-Uni, cet article montre que si la rotation de la main-d'œuvre a diminué en réponse à la pandémie, la réallocation des emplois est restée connectée à la productivité des entreprises –autrement dit, les entreprises à productivité élevé ont eu d'avantage tendance à se développer alors que les entreprises à faible productivité ont eu d'avantage tendance à se contracter. La pandémie a coïncidé avec un renforcement de la relation entre réallocation et productivité en Australie (de façon temporaire) - mais a un affaiblissement de cette relation en Nouvelle-Zélande - qui semble lié à la conception des dispositifs de maintien dans l'emploi. Enfin, les entreprises utilisant intensivement des applications pour gérer leur entreprise se sont révélées plus résilientes, y compris lorsque l'on contrôle pour la productivité. Ainsi, alors que les mesures de politiques publiques ont partiellement gelé le processus de destruction-créatrice, la nature du choc - pendant lequel il était essentiel d'être connecté et en mesure d'opérer à distance- a favorisé les entreprises à haute productivité et à la pointe de la technologie, entraînant une réallocation de la main-d'œuvre vers ces entreprises. L'utilisation de données nouvelles et en temps quasi-réel pour examiner les effets de la pandémie sur l'allocation des ressources constitue une avancée significative, en particulier considérant que l'article fondateur examinant l'effet de la réallocation sur la productivité pendant la Grande Récession est arrivé près de six ans après l'effondrement de Lehman Brothers.

Classification JEL: E24, E32, J63, O4.

Mots Clés: COVID-19, productivité, réallocation, récessions.

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COVID-19, Productivity and Reallocation: Timely evidence from three OECD countries

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1. Introduction

1. The impact of the COVID-19 shock on small firms is a key policy concern. Indeed, small business resilience to the shock will not only shape the trajectory of the near term economic recovery but also the longer run consequences for potential output. The nature of resilience will partly depend on productivity. Productivity is about "working smarter" – rather than "working harder" – to produce more output by better combining inputs, owing to new ideas, technological innovations and organisational practices. In the context of the pandemic, high productivity firms – due to their superior managerial practices – may be more able to effectively accommodate teleworking and nimbly adapt their business models to social distancing. This would reinforce the process of productivity-enhancing reallocation – the tendency for more productive firms to expand and less productive firms to contract (or exit). While Schumpeter (1939) proposed that recessions can accelerate this process – if markets increasingly select (scrap) the most (least) productive firms – a key concern is that credit frictions may lead productive but financially fragile firms to contract, and underpin the exit of young and small firms before they realise their innovative potential (Ouyang 2009).

2. Evidence on the role of productivity in shaping small business resilience to the pandemic is limited due to a lack of suitable data. In this paper, we fill this gap by exploiting novel high frequency indicators on workforce outcomes merged with pre-pandemic measures of firm-level labour productivity. These data are sourced from Xero Small Business Insights (Xero SBI), which draws on anonymised and aggregated accounting and payslip data from small businesses that subscribe to Xero – a cloud-based accounting software platform for small businesses.[2] This allows us to explore how the COVID-19 shock shaped the nature of productivity-enhancing reallocation in Australia, New Zealand and the United Kingdom. While the sample comprises mainly smaller firms, this is an economically relevant group that has arguably been most exposed to the pandemic.

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[2] Data are fully anonymised. Furthermore, the accounting data – more specifically, entries on the general ledger (e.g. each revenue item) – are aggregated for each firm to monthly frequency (rather than individual transactions) to ensure no possibility of identification.

3. We model dynamic allocative efficiency by estimating the responsiveness of firm-level employment changes to (pre-pandemic) labour productivity, while controlling for the differences in the nature of the shock across country-region-industries and firm size classes. Applying this model to Australian data, Andrews and Hansell (2021) demonstrate a strong connection between (within-industry) labour reallocation and firm-level productivity over 2002-2016, which significantly boosted aggregate productivity growth. But how did the pandemic affect the reallocation-productivity link, especially in light of the prevalence of job retention schemes – which aimed to reduce job destruction and thus reallocation – in Australia, New Zealand and the United Kingdom?

4. Overall, while job reallocation and creative destruction fell following the onset of the pandemic – with static firms becoming more prevalent – job reallocation remained firmly linked to productivity. On average across countries over the year to February 2021, the implied difference in employment growth between a high productivity firm – i.e. one with labour productivity (LP) one standard deviation above the industry mean – and a low productivity firm – i.e. one with LP one standard deviation below the industry mean – was 6.8 percentage points. While this differential reflects the strong tendency for job losses to be concentrated in the least productive quartile of firms, high productivity firms were also more likely to expand their workforce over the course of the pandemic. The link between workforce adjustments and productivity is also evident in hours worked at the firm level – a novel variable in the Xero database. We also document a temporary acceleration in productivity-enhancing reallocation over the first half of 2020 (relative to the same period in 2019), which is partly due to dynamics within industries hard-hit by the pandemic, such as Hospitality and Arts & Recreation. These patterns are broadly consistent with Schumpeter's cleansing hypothesis, which predicts that the reallocation-productivity link to strengthen with the size of the recessionary impulse.

5. Cross-country differences emerge in the pandemic's impact on job reallocation and productivity. The temporary surge in the reallocation-productivity link over the first half of 2020 is largely driven by Australia. By contrast, the onset of the pandemic in New Zealand is associated with a weakening of reallocation-productivity link (compared to the corresponding period in 2019). We document a more extensive "hibernation" of the New Zealand economy over the initial months of the pandemic, as reflected in a sharp increase in the prevalence of static firms, whereas firm contraction was more common in Australia. These patterns may partly reflect the earlier introduction of New Zealand's job retention scheme, which also protected a greater share of the workforce than in Australia. But these cross-country differences should not be overplayed as they had largely faded by late 2020. In fact, over the year to February 2021, the extent of productivity-enhancing reallocation is strongest in the United Kingdom, which may reflect the relatively larger macroeconomic shock.

6. Technology adoption is also key to resilience, with employment and hours worked holding up more amongst firms that intensively use apps to manage their business (e.g. E-commerce and cashflow reporting and management apps), even after controlling for productivity. App usage could be a sign that firms are undertaking learning-by-doing and making significant intangible investments, which will only crystalize a market return – and thus be reflected in productivity – in the future. This budding organisational and technological capability may have enabled such firms to nimbly adjust to changing market conditions and seize new growth opportunities – for example, related to online sales – induced by the pandemic.

7. Overall, productivity and technology were important determinants of small business resilience to the pandemic. This is consistent with the idea that COVID-19 accentuated the importance of firm capabilities and organisational capital by forcing a wave of experimentation with "novel modes of business, work, consumption and communication" and accelerated digital transformation (Barrero et al 2020). High productivity firms – due to their superior managerial practices (Bloom and Van Reenen, 2007) – and tech-savvy firms could more effectively adjust, which enabled them to capitalise on new growth opportunities. Indeed, while policy partly suppressed the rate of creative destruction, the nature of the shock – i.e. one where being online and able to operate remotely – played to the strengths of high productivity and tech-savvy firms. Thus, we observed a reallocation of labour to such firms, despite a policy response that

emphasised preservation over reallocation. These findings are also significant, given that an indiscriminate shakeout of high productivity and tech-savvy firms – and the associated destruction of firm-specific intangible capital – would have imparted lasting scars and made it more difficult to accommodate behavioral changes induced by the pandemic via the development of new business models.

8. Finally, we leverage Xero's unique information on worker tenure and employment contract type to study the interplay between Australia's job retention scheme and productivity-enhancing reallocation dynamics. Short-tenure casual workers did not qualify for the JobKeeper payment, which allows us to distinguish between the pool of workers that were eligible and ineligible for the job retention scheme. Amongst the pool of ineligible workers, we document a pronounced acceleration in productivity-enhancing reallocation dynamics following the onset of the pandemic. Underlying this is a sharp employment contraction amongst the lowest productivity quartile, which is consistent with the cleansing dynamics that may characterise unfettered markets in the face of a very large adverse shock. But we also find that productivity-enhancing reallocation intensified amongst the pool of eligible workers following the onset of the pandemic. While this finding is surprising, it is consistent with evidence presented in Andrews, Bahar and Hambur (2021) which shows that higher productivity firms were more likely to participate in the initial phase of the JobKeeper scheme. While further research is required to investigate in the context of Xero SBI, this raises the prospect that JobKeeper disproportionately shielded *higher* productivity firms from the shock.

9. Our contribution is threefold. First, we supply novel near-real-time insights on the impact of the pandemic on productivity-enhancing reallocation in three countries. This is significant given that the seminal paper on the impact of the Great Recession on productivity-enhancing reallocation in the United States first appeared – in working paper version – some six years after Lehman Brothers collapsed (Foster et al., 2014). Second, we add a cross-country dimension to the nascent literature and introduce novel variables on hours worked and technological adoption at the firm level which are unique to Xero SBI. Finally, we provide systematic near-real-time evidence on the nature of the reallocation-productivity link across different groups of workers, according to their potential eligibility for the job retention schemes.

10. The next section reviews evidence on the nature of the reallocation process and how it varies across the business cycle. Section 3 describes the Xero SBI database and presents some preliminary cross-country evidence on small business performance during the pandemic. Section 4 then describes the empirical methodology that we exploit to produce new evidence on reallocation-productivity link since the onset of the pandemic. Section 5 explores the potential impact of Australia's Job Retention Scheme on the process while the final section offers some concluding thoughts.

2. Productivity, reallocation and economic shocks

2.1. Well-functioning economies reallocate resources to more productive uses

11. Well-functioning market economies are characterised by a resource reallocation process that has two key dimensions. First, the pace of reallocation is typically high, with headline economic statistics concealing an intense churning of jobs and firms, as successful market activities are sorted from unsuccessful ones. Across the OECD, gross job creation and job destruction rates averaged 12% and 10% respectively over 2004-2007, with these figures reversing as the crisis took hold (Criscuolo, Gal and Menon 2014). Firm dynamics make an important contribution to the reallocation process, with new firms typically accounting for one-quarter of gross job creation, while one-third of gross job destruction is due to firm exit.

12. Second, this reallocation process is strongly linked to firm-level productivity. A wealth of empirical evidence shows that high productivity firms are more likely to expand and low productivity firms are more likely contract and exit (Decker et al., 2020). These empirical studies take their structure from two rich

theoretical literatures: *i*) the canonical models of firm dynamics,[3] whereby idiosyncratic shocks to productivity, demand, and costs impacts the growth and survival of heterogeneous firms; and *ii*) the adjustment cost literature for employment dynamics, which predicts that, conditional on initial size, plants with positive productivity shocks are more likely to grow (Cooper, Haltiwanger, and Willis 2007).

13. There is much potential for resource reallocation from low to high productivity firms to raise aggregate productivity due to the widespread heterogeneity in firm-level productivity. For example, even within narrowly defined industries (that is, ready-mix concrete) in the United States, firms at the 90th percentile of the multi-factor productivity (MFP) distribution are twice as productive as firms at the 10th percentile (Syverson, 2004). Such large differences in productivity could be sustained in equilibrium by imperfect product substitutability that prevent customers from easily shifting purchases between producers and supply-side factors related to technology shocks, management skill and R&D (Bartelsman and Doms, 2000). But more recent studies emphasise that a few star performers disproportionately drive aggregate growth (Haltiwanger et al, 2013), while recognising that many technologies remain unexploited by a large share of firms (Andrews, Criscuolo and Gal, 2016).

14. While the source of these within-firm differences in productivity is complex, the contribution of within-industry resource reallocation from low to high productivity firms to aggregate productivity growth is significant. Bailey, Hulten and Campbell (1992) found that over a five-year period about half of a typical US industry's MFP growth was due to the reallocation of factors between plants, rather than within-plant productivity growth, while studies for other countries yield similar conclusions.[4] By contrast, there is less scope for growth-enhancing between-sector reallocation (Foster, Haltiwanger and Krizan, 2001; Mora Sanguinetti and Fuentes, 2012).[5]

15. These gains to aggregate growth from reallocation are crucial given that reallocation entails costs, which are politically salient. Indeed, the growth of productive firms is necessarily accommodated by via the downsizing or market exit of other firms, which can result in job destruction that may entail: *i*) persistent earnings losses (Jacobson et al, 1993), as getting knocked-off a partially climbed job ladder leads to a loss of firm-specific human capital, high quality job matches and back-loaded compensation (Carrington and Fallick, 2014); and *ii*) negative social outcomes with respect to life expectancy, marital stability, emotional well-being and the education outcomes of displaced workers' children (Davis and von Wachter, 2011).

16. It is in this context that the productivity slowdown – observed in OECD countries over the past two decades – is particularly significant. Underpinning this trend is a decline in job reallocation, which partly reflects lower firm entry as new firms create outside options for workers to switch jobs. But the connection between job reallocation and productivity has also weakened over time in a number of OECD countries (Decker et al, 2020; Andrews and Hansell, 2021). For example, the declining (within-industry) reallocation of labour from less productive to more productive firms can account for one-quarter Australia's productivity slowdown after 2012 (Andrews and Hansell, 2021). It is against this background that the question of how the COVID-19 shock will affect productivity – via the reallocation channel – looms large.

[3] See: Jovanovic (1982); Hopenhayn (1992); Hopenhayn and Rogerson (1993); Ericson and Pakes (1995).

[4] In the United Kingdom, this reallocation process accounts for over 80 per cent of MFP growth in the manufacturing sector (Disney et al, 2003). Baldwin and Gu (2006) find that this reallocation accounts for about 70 per cent of aggregate labour productivity growth in Canada. Foster et al (2006) find that entry and exit explain almost all labour productivity growth of the US retail sector.

[5] This reflects the tendency for: *i*) factors to be inherently more substitutable within industries; and *ii*) within-sector differences to dwarf between-sector differences in firm behaviour

2.2. Shocks can influence the reallocation process

17. The process of reallocation can vary with the economic cycle. On the one hand, recessions can provide a fertile breeding ground for restructuring if markets select (scrap) the most (least) productive firms yielding the so-called cleansing effects (Caballero & Hammour 1994). Recessionary episodes in the United States from the 1940s to the early 2000s generally displayed such cleansing dynamics.[6] Reallocation accelerated – as the rise in job destruction more than offset the decline in job creation – and was strongly linked to productivity, with job destruction and exit concentrated in lower productivity business units.

18. On the other hand, recessions may be less benign due to sullying or scarring effects. This can arise if fewer high quality job matches are created (Barlevy 2002) or if credit frictions lead productive but financially fragile firms to disproportionately contract or exit (Barlevy 2003). While recent evidence suggests that the latter may not be sufficient to overturn the cleansing effect (Osotimehin and Pappada 2015), it is notable that reallocation fell during the Great Recession – with the decline in job creation outweighing the rise in job destruction – and there was a weaker link with productivity, especially amongst young firms (Foster, Grim and Haltiwanger, 2016). Indeed, recessions – particularly financial crises – might impart scars if they reduce entrepreneurial finance (Buera and Moll, 2015) and disrupt the fragile post-entry learning-by-doing process (Ouyang, 2009), leading to a “lost generation” of firms (Sedláček, 2020). Even so, there are examples of successful start-ups emerging during downturns testament to the ability of young firms to nimbly respond to changing market conditions (Calvino, Criscuolo and Verlhac, 2020).[7]

19. While the evidence on the impact of recessions on reallocation is mixed, it is vital that churn remains connected to firm productivity in order to offset the damage that recessions may impart on the intangible capital stock. By accelerating job destruction and business closures, recessions can lead to losses of job-specific capital and organisational capital – both internal (i.e. tacit knowledge) and external (i.e. supply chain connections) to the firm. These costs – which can undermine recovery and scar the economy’s productive fabric – are compounded when the process of business downsizing and exit is not driven by productivity, as there is no scope for productivity-enhancing reallocation towards more efficient producers on the other side (Syverson 2020).

20. If history is any guide, evidence on the impact of the pandemic on reallocation and productivity is still many years away. This partly reflects the lengthy time lags that characterise the release of suitable microdata sources, with (BLS) establishment-level and (Census Bureau) firm-level data on business deaths in the United States during mid-2020 not slated for release until late 2021 and 2023 respectively (Crane et al, 2020). Consequently, the seminal research on the effect of the GFC on reallocation in the United States was only released – in working paper version – some six years after the collapse of Lehman Brothers (FGH 2014). But as discussed below, the emergence of novel high frequency firm level datasets may allow a more timely read on the impact of the pandemic on productivity-enhancing reallocation.

2.3. COVID-19, productivity and reallocation

21. The impact of the pandemic on the process of productivity-enhancing reallocation is theoretically ambiguous. On the one hand, the COVID-19 shock may have severely disrupted the typical reallocation process that characterises well-functioning market economies. In this view, the pandemic was a health shock that was truly exogenous to pre-crisis firm performance and the collapse in mobility that followed – a function of both fear and arbitrary lockdowns – affected all firms, regardless of their productivity. This was reinforced by a crisis economic policy response that prioritised preservation (or hibernation) via job

[6] See: Davis and Haltiwanger (1990, 1992 and 1999); Davis, Faberman, and Haltiwanger (2006, 2012); Foster, Haltiwanger, and Krizan (2001); and Davis, Haltiwanger, and Schuh (1996)

[7] For example, Dropbox, Uber, Airbnb, WhatsApp, Groupon, and Pinterest were all founded during or just after the Global Financial Crisis, while Alibaba’s Taobao that was founded during the SARS outbreak in China in 2003.

retention schemes – which maintained connections between workers and firms – and various measures to shield firm finances and prevent foreclosure. These forces had two consequences. First, the job reallocation rate fell significantly, as job destruction was effectively curbed while there was limited scope for job creation. Second, the reallocation-productivity link was diminished, if not completely severed.

22. An alternative view posits that the reallocation-productivity link remained – even if the overall rate of reallocation fell – as the nature of the shock accentuated the importance of firm capabilities and organisational capital. COVID-19 forced a wave of experimentation with “novel modes of business, work, consumption and communication” and accelerated digital transformation (Barrero et al 2020). High productivity firms – due to their superior managerial practices (Bloom and Van Reenen, 2007) – could more effectively accommodate teleworking and nimbly adapt their business models to social distancing, which enabled them to capitalise on new growth opportunities. Better managed firms may have also been more able to capitalise on the range of policy support measures available.

23. Evidence on the impact of the pandemic on productivity via the reallocation channel is so far limited but is broadly consistent with the idea that reallocation declined but remained connected to productivity. In terms of job reallocation rate, the most systematic evidence comes from Australia, which shows a significant decline in the job reallocation rate over 2020. From February 2020, job creation declines significantly while the job destruction rate initially rises sharply before falling following the announcement of JobKeeper on 29 March 2020. Real time cross-country evidence on job destruction is scarce but the fact that the unemployment rate rose by less than 2 percentage points in many OECD countries – in the face of the large macroeconomic shock – is consistent with a muted response on the destruction margin.

24. Bloom et al (2021) exploit survey data from the Decision Maker Panel – a large and representative monthly panel survey of UK firms from 2016 – to study the implications of the pandemic for productivity in the United Kingdom. Focusing on incumbent firms, they show that hours worked falls more sharply in 2020-Q2 for firms that had lower productivity (over 2017-2019). While this partly reflects the fact that pandemic hit lower productivity sectors harder, the connection between hours worked contraction and firm productivity is also observed within sectors. Evidence from France shows that although the number of firms filing for bankruptcy was well below its normal level since the pandemic, the factors that predicted firm failures in 2019 – primarily low productivity and debt – were at work in a similar way in 2020 (Cros, Epaulard and Martin, 2021). Hong, Kikuchi and Saito (2021) reach similar conclusions for Japan. Finally, better managed firms in Italy experienced smaller declines in expected sales during the post-lockdown period, which may partly reflect their ability to provide effective monitoring and incentive structures to support productive teleworking (Lamorgese et al, 2021). The paucity of evidence partly reflects the fact that few real time datasets contain information on firm-level productivity, which is essential to fully explore the reallocative consequences of the pandemic.[8]

3. High-frequency firm-level data

3.1. Xero Small Business Insights data

25. Timely analysis of the impact of the pandemic on productivity-enhancing reallocation has been limited by the lack of suitable microdata, and in particular measures of firm-level productivity. But we have a unique opportunity to shed light on this question by using anonymised and aggregated near-real-time

[8] Bartik et al (2020) speculates that the pandemic may have engender cleansing effects in the United States on the basis that firms with weak sales growth in 2019 were more likely to shutdown at the peak of the first wave of the pandemic and subsequently less likely to re-open during the “recovery”.

microdata from Xero – a cloud accounting platform with more than 2.7 million global subscribers.[9] Xero are responsible custodians of their customer's sensitive data and take precautions to ensure the data that they receive are not disclosed in any way that could identify individual businesses. Through Xero, small business owners and their advisors have access to real-time financial data any time, anywhere and on any device. Xero offers an ecosystem of over 1,000 third-party apps and 300 plus connections to banks and other financial partners. Merging the revenue and payslip data yields a near-real-time firm-level dataset that contains quantitative measures of: revenue, employment, hours worked, wages, employment arrangements (full-time, part-time and casual plus worker tenure) and industry/location codes.[10] It is also possible to explore technology adoption, with data on the number of cashflow reporting and management apps (i.e. Cashflow, Inventory, Square) and E-Commerce apps (i.e. Shopify, Stripe, WooCommerce) a firm has connected to their Xero account. Xero is broadly representative of the small business community – in terms of firm size and industry coverage (see below). We use data on small businesses in Australia, New Zealand and the United Kingdom, aggregated to monthly frequency from 2018 until February 2021.

26. It is difficult to overstate the novelty of the Xero dataset. The timeliness of its employment and revenue indicators represents an improvement on existing private sector datasets (e.g. ORBIS), and allows us to construct revenue per worker – a basic measure of (revenue-based) labour productivity. And the measures of hours worked, employment arrangement and technology usage are rarely available in the extant firm-level data sources.[11] Because it is based on accounting and payslip data, the data are of high quality and granularity and can be analysed in close to near-real-time. With its workforce information, Xero has the hallmarks of a nascent linked employee-employer dataset – the gold standard of modern administrative microdata sources – but with the added benefits of a cross-country and high frequency dimension.

27. Xero also has features – some of which are common to other private sector firm-level datasets – that should be kept in mind when using for economic research. First, like other private sector datasets, Xero's coverage expands over time, as new customers join the platform, and a firm's entry or exit from the dataset does not necessarily imply market entry and exit. Second, Xero is a non-random sample of firms, comprising mainly smaller firms, which – given their use of cloud accounting software – are likely to be more tech-savvy and productive (and possibly younger) than the typical small firm. But non-random selection is also a feature of other private sector firm-level datasets (such as ORBIS), which tends to better capture medium-sized and larger firms, while the small firms that feature tend to be more productive. While this should be kept in mind when looking to draw aggregate implications, smaller firms are clearly an economically relevant group as they were particularly exposed to the COVID-19 shock. For example, high frequency tax data curated by the Australian Bureau of Statistics show that between early March and late April 2020, Single Touch Payroll jobs fell by 10.5% amongst small firms (less than 20 employees) but only 4.5% amongst large firms (i.e. 200 employees and above).

28. Figure 1 compares the distribution of firms in the Xero Small Business Insights data to that in the official (business register data) sourced from National Statistical Offices in each country, according to firm size bucket as defined by number of employees. Not all subscribers to Xero are in the Xero Small Business Insights dataset that we use for our analysis; as such, the comparison below should not be read as

[9] Data are fully anonymised, and the accounting data are aggregated for each firm to monthly frequency (rather than individual transactions) to ensure no possibility of identification.

[10] Industry and location data are self-reported by firms in Xero.

[11] The hours worked variable is constructed by taking the number of hours paid on employee payslips. However, not all firms use "hours" as the unit of measure on payslips; for example, some firms use "days" as the unit for salaried employees, but this is still reported in the hours field in the payslip. One consequence is that while it can be used to track changes in hours worked within firms (since units are consistent), it is not informative of between-firm comparisons in hours worked.

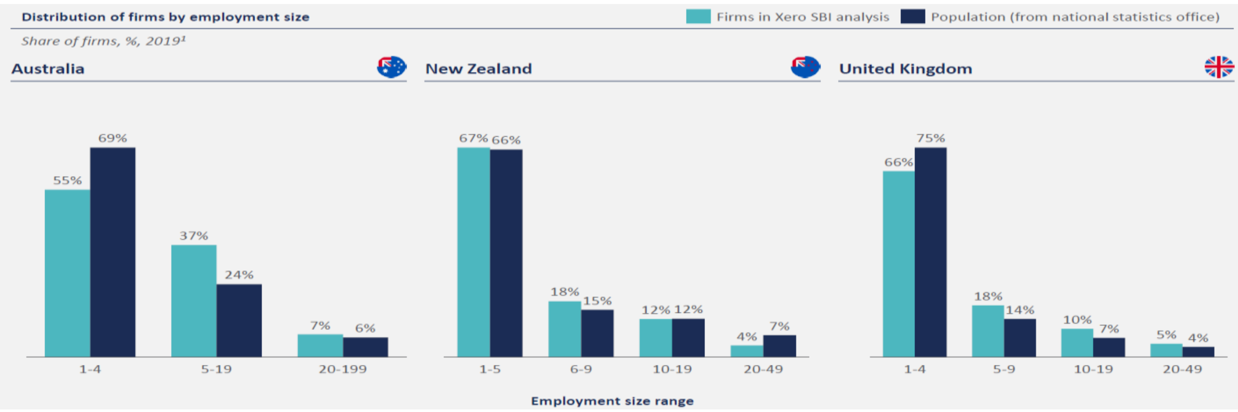
indicative of Xero's customer base overall. While the Xero Small Business Insights dataset we use appears broadly representative of the small business population, some modest differences emerge. Focusing on New Zealand and the United Kingdom where more narrowly-defined firm size classes are available, Xero tends to be moderately overweight on firms with 5-19 employees, than other small firm size classes. The same is also true for Australia. Xero's industry coverage is also broad-based, drawing a reasonable proportion of firms from all industries, and crucially those industries centred on the delivery of in-person services that have been hard-hit by the pandemic (such as Hospitality and Arts & Recreation; see Figure A.1 of Annex A). Again, some differences emerge with the official sources, with Xero over-weight on firms in construction in Australia and New Zealand and professional services in the United Kingdom.

29. As discussed below, our econometric framework – through the inclusion of country, industry and firm size fixed effects – allows us to control for these moderate differences in coverage, by focusing on firm dynamics within industry and firm size classes in a given country. We also confront the expanding coverage of firms over time by presenting alternative estimates based on a fixed sample of firms, although this issue does not loom large given that we only utilise three years of data. Moreover, the baseline results for Australia are consistent with Andrews, Bahar and Hambur (2021), who conduct a similar exercise on a broader sample of firms drawn from administrative tax data.

30. We implement a range data cleaning techniques that are customary in the literature including winsorising key economic variables – such as revenue per worker – at the top 1% and bottom 1% of the within-industry distribution.[12] To ensure data quality, we filter the data such that firms must: *i*) post revenue for at least 6 of the 12 months in calendar 2019 (not all firms will earn revenue every month); *ii*) be either a sole trader, partnership, company or not for profit (e.g. we exclude trusts and other unspecified corporate structures); *iii*) be a paying subscriber of Xero (we exclude those on a free trial); and *iv*) have an advisor (e.g. accountant or bookkeeper) linked to their Xero account.

Figure 1. Distribution of firms by employment size

Share of firms (%), 2019



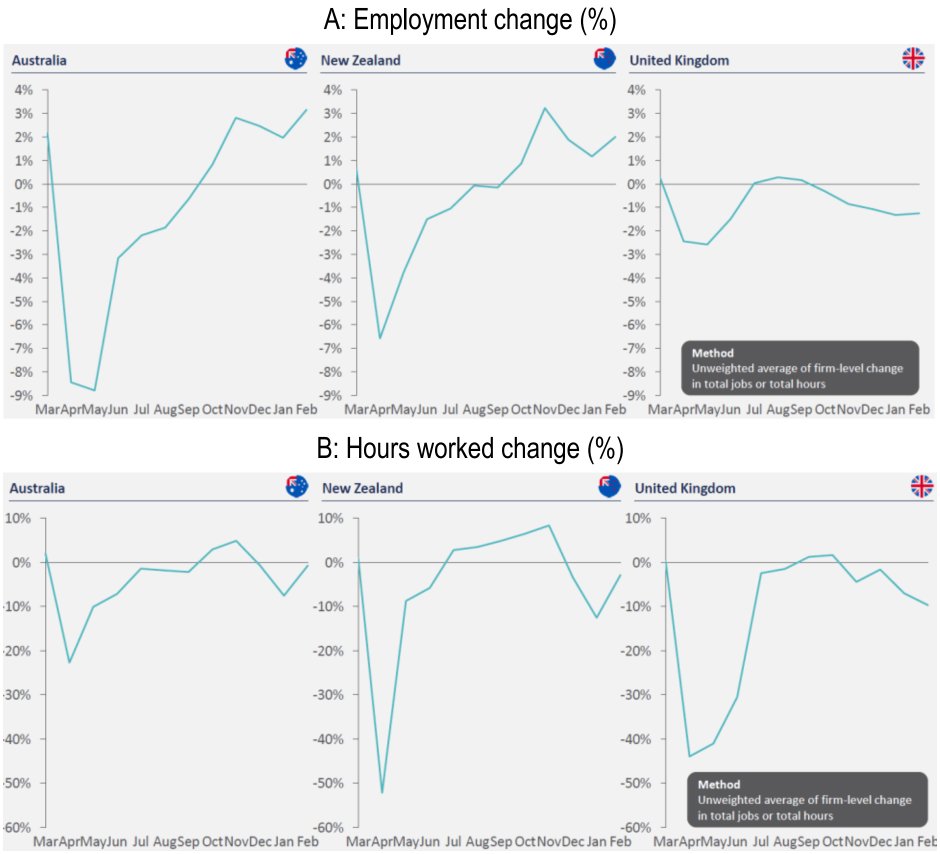
Note: The figure compares the distribution of firms by size in the subset of the Xero SBI data that we use to official sources for each country. Shares are normalised to exclude larger business.
Source: Authors calculation based on Xero SBI and National Statistical Offices.

[12] Winsorising is an outlier adjustment methodology that effectively recodes values above (below) 99th (1st) percentile of the distribution to the value of the 99th (1st) percentile.

3.2. SME performance over the pandemic

31. By way of background, Figure 2 plots the unweighted average of firm-level changes in total jobs and hours worked since February 2020. Panel A shows significant declines in average small business employment from February through to April in New Zealand and into May in Australia and the United Kingdom before a recovery takes place. Across countries, average hours worked falls even further than heads (Panel B), consistent with the widespread use of wage subsidy or job retention schemes. Finally, Figure A.2 of Annex A shows that the COVID-19 shock is also reflected in sharp declines in average turnover across firms in April (Panel A), with hospitality particularly hard-hit (Panel B).

Figure 2. Average within-firm workforce growth since February 2020



Notes: Measured as unweighted average firm-level change in relevant dependent variable. We count an employee as "employed" for the relevant month if they received a payment from their employer; this means employees working zero hours, but receiving payments through the relevant wage subsidy scheme count as "employed".
Source: Authors calculation based on Xero SBI data.

32. Despite a range of methodological differences, the trajectory of these workforce indicators in Xero is broadly consistent with official data from national statistical offices, suggesting that the Xero dataset plausibly captures the COVID-19 shock. Taking Australia as an example, weekly data from Single Touch Payroll shows compared to February 2020, total employment in the 0-20 employment size class was around 7.5% lower on average over April 2020 to May 2020 (versus –8½% in Xero) before recovering to be around 2.7% higher over the year to February 2021 (which is similar to Xero).[13] While Australia's Labour

[13] Statistics New Zealand's experimental weekly employment indicators release shows that relative to February 2020, the total number of jobs was on average 4.5% lower in April 2020 and on average around 3% higher in February 2021

Force Survey does not contain a breakdown of hours worked by firm size, a similar profile is observed in the total economy measure which shows a fall in hours worked of around 17% between February and April 2020 before recovery to broadly flat over the year to February 2021. Xero shows a more marked decline in hours worked between February and April 2020 (-22%), but this should be expected given that small firms were harder hit by the pandemic.[14]

33. As is now well established, the labour market shock was buffered by the use of wage subsidy or job retention schemes in each country. These schemes preserved the connection between workers and firms – despite a sharp pandemic-induced economic downturn – with many workers on drastically reduced hours. By curtailing job destruction, job retention schemes can be effective crisis tools; but, these schemes need to be temporary to ensure that they do not unintentionally impede job creation during recovery by trapping scarce labour in low productivity firms. Indeed, the announcement of Australia's JobKeeper scheme in late March 2020 was followed by a sharp reduction in job destruction; but it is significant that job creation rates continued to fall (Australian Treasury 2020). Thus, transitioning away from job retention schemes towards policies that promote labour reallocation is important (Australian Government Budget 2021). Barrero, Bloom and Davis (2020) highlight the risk that policies designed for the height of the recession outstay their welcome and distort incentives to seek new employment, while policies that facilitate reallocation of labour can improve the speed of the recovery.

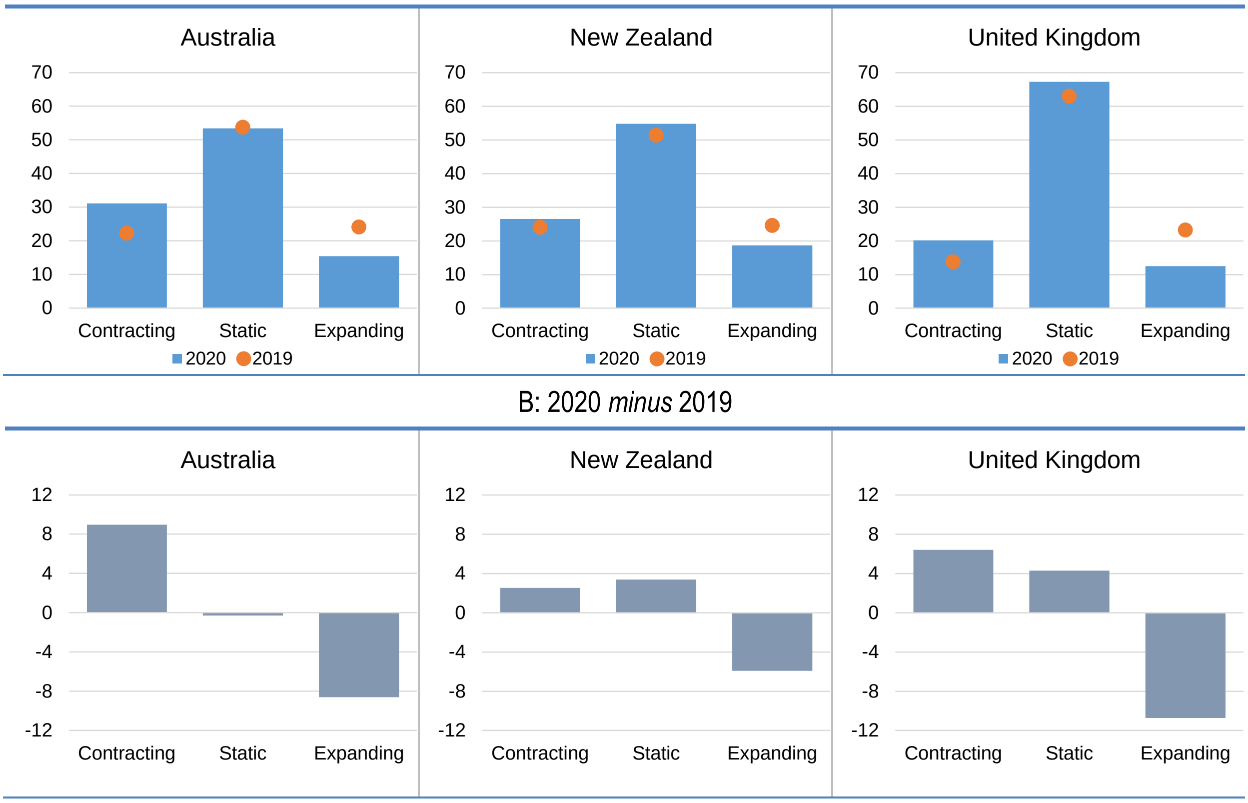
34. To dig deeper, we analyse changes in the firm employment growth distribution over 2019 and 2020, by collapsing firms into three groups: contracting, static and expanding firms. The job reallocation rate is proxied by the sum of the contracting and expanding shares, and is inversely related to the static share. Between February and May 2020, the share of expanding firms (i.e. those adding workers) declined in each country relative to the same period in 2019 (Figure 3). In New Zealand, there were increases in the share of static firms and contracting firms to a lesser extent, while in the United Kingdom the share of contracting firms rose by more than the share of static firms. By contrast, the share of contracting firms rose sharply in Australia, while the share of static firms was little changed. These patterns are consistent with later announcement of Australia's wage subsidy scheme (30 March) than in New Zealand (17 March) and the United Kingdom (20 March) and the less broad-based coverage of the workforce in Australia (OECD (2020); see Figure A.3 of Annex A and Section 5).

(based on the "Number of paid jobs - 20 days" series). This is broadly consistent with Figure 2 but some differences are expected as Statistics New Zealand's measure is based on all firms. Statistics New Zealand's series reaches at trough in the week ending 26 April 2020, which is around 9% lower compared to the week ending 1 March 2020.

[14] ONS data for the United Kingdom show that aggregate hours worked peaked in the December 2019 to February 2020 period, and subsequently declined to be 20% lower in April to June 2020 period and 8.8% lower in the December 2020 to February 2021 period relative to the peak (based on "LFS: Total actual weekly hours worked" series).

Figure 3. Distribution of firm-level employment growth initially after the onset of the pandemic

A: February to May, 2020 and 2019



Notes: The Figure shows how the distribution of firm employment growth between February and May changed between 2019 and 2020. It shows the share of firms across three groups according to the trajectory of the employment headcount between February and May in each year (contracting=decreased headcount, static=unchanged headcount; expanding=increasing headcount).
Source: Authors calculation based on Xero SBI data.

35. While these data imply an initially larger fall in job reallocation in New Zealand and the United Kingdom, by the end of 2020 Australia's firm growth distribution became more static and resembled that of New Zealand (Figure 4). In Australia, the share of static (expanding) firms rose (fell) by around 1 percentage point and the contracting firms were little changed between February 2019 and February 2020, compared to the same period in 2019. But in the United Kingdom, there was a sharp rise in the share of contracting firms (+4.4%pts) and a much more modest increase in the share of static firms (+1.7%pts) over the same period.

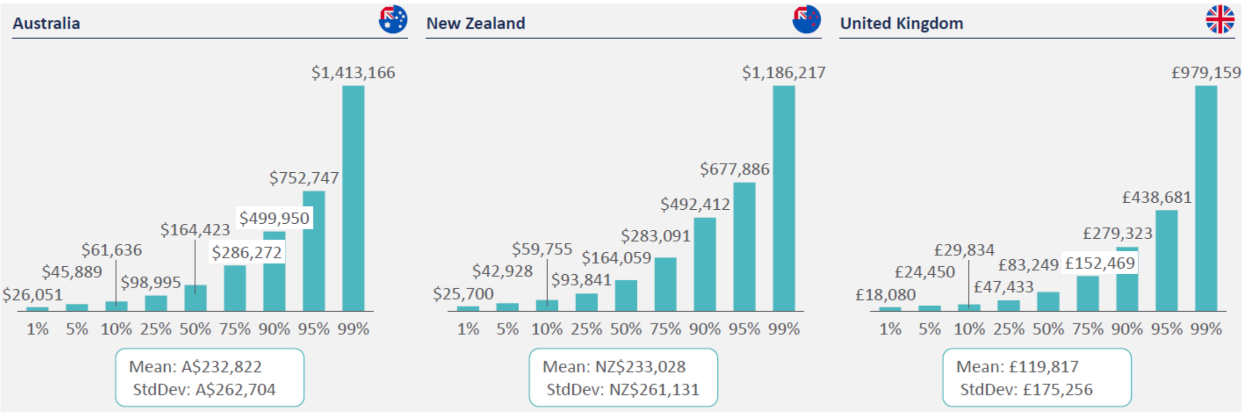
Figure 4. Distribution of within-firm employment growth: pre vs post-pandemic

Note: The figure shows how the employment growth distribution over the year to February shifted between 2019/20 and 2020/21, based on the same methodology outlined in Figure 3.
Source: Authors calculation based on Xero SBI.

36. While the pandemic was associated with a fall in the overall rate of job reallocation, it did not completely freeze creative destruction: a non-trivial share of firms were still adding and shedding workers, even at the peak of the first wave of the pandemic. This diversity in net job creation at the firm-level is significant in light of the widespread heterogeneity in firm productivity within narrowly-defined industries (Syverson 2011). This diversity creates scope for growth-enhancing resource reallocation towards more productive firms. Unsurprisingly, there is also much heterogeneity in productivity amongst small businesses in the Xero SBI, with a firm at the 75th percentile of the within-industry labour productivity distribution producing around three times as much revenue per worker than the firm at the 25th percentile of the distribution (Figure 5). The remainder of the paper explores how firm-level workforce adjustments were connected to a firm's rank in the (within-industry) labour productivity distribution.

Figure 5. Widespread heterogeneity in firm productivity within industries

Revenue per worker in 2019 (local currency units)



Note: The figure shows the distribution of firm-level labour productivity for each country, which is calculated by taking the average of the industry-level distribution in each country.
Source: Authors calculation based on Xero SBI.

4. COVID-19 and productivity-enhancing reallocation dynamics

4.1. Empirical approach

37. As discussed above, there is much evidence that conditional on initial firm size, high-productivity firms are more likely grow and low-productivity firms are more likely to contract and exit. We apply the workhorse econometric model from this literature to Xero high frequency firm level data to explore the potential impact of the pandemic on the (within-industry) connection between job reallocation and productivity in three countries.[15] More formally, this involves estimating the following baseline equation:

$$\Delta E_{isr}^{Feb:j} = \alpha + \beta LP_{isr} + FE + \varepsilon_{isr} \quad (1)$$

Where: E is cumulative change in log employment between February 2020 and subsequent points (i.e. j=May 2020 or j=February 2021) in firm *i*, industry *s*, and location *r*. Industry categories are ANZSIC divisions (outlined in Figure A.1 of Annex A) while the location correspond to states in Australia and regions in New Zealand and the United Kingdom.[16] LP is the log level of firm-level labour productivity in 2019,

[15] The various approaches to measuring allocative efficiency take their structure from either the: *i*) Olley and Pakes (1996) covariance approach; *ii*) Hsieh and Klenow (2009) dispersion in marginal revenue products approach; or *iii*) Baquee and Fahri (2020) mark-up based approach. While no approach is perfect, practical feasibility leads us to employ the first approach. Nevertheless, we note the potential caveats related to linear revenue function assumptions. Under constant returns to scale and perfect competition, the firm with the highest average productivity also has the highest marginal productivity, which implies that shifting resources to the most productive firm will raise aggregate productivity. But with imperfect competition, as resources shift to the most productive firms, marginal revenue products increase (or decrease) for the least (or most) productive firms.

[16] For example, regions in New Zealand are the 16 government regions. In the United Kingdom, regions are the 9 regions of England plus Northern Ireland and Scotland.

computed as revenue per worker, while FE denote fixed effects defined below.[17] If β>0, job reallocation and productivity are connected within industries: more productive firms are more likely to expand and less productive firms are more likely to shed labour, suggesting that reallocation is productivity-enhancing. We also estimate a specification with dummy variables corresponding to the firm's quartile in the (within-industry) labour productivity distribution (in place of the log level of LP). We then use the estimated coefficients to chart how the workforce adjusts across each productivity quartile – after controlling for a range of factors (see below) – before and after the pandemic.[18] This more flexible specification allows us to investigate potential non-linearities in workforce adjustments across the firm-level productivity distribution.

38. The model includes a highly demanding fixed effects (FE) structure, that interacts firm size classes based on 2019 employment (1-4, 5-9, 10-14, 15-19, 20+ employees), industry and location dummies. This allows us to control for differences across locations (i.e. regions within countries), industries and firm size classes in the shock process and data coverage. In equation [1], we estimate how employment adjustments are linked to (lagged) firm-level productivity within location*industry*size cells (group 1). This effectively sweeps out average outcomes at the cell level, which allows us to control for the fact that the pandemic hit firms of a given size harder in the hospitality sector in London than in Auckland. For each model, standard errors are clustered at the group level.

39. We explore various sources of heterogeneity in the reallocation-productivity link. First, we test if the strength of the link varies *across countries* by interacting LP with country dummies, and *across industries* by interacting LP with a dummy variable for those industries hit particularly hard by the pandemic (i.e. accommodation and food services, arts & recreation services, and other services). Second, to explore potential asymmetries in the link between employment adjustments and firm productivity, we re-estimate equation [1] using two alternate dependent variables, specifically a dummy variable that equals one if a firm: i) expanded, zero otherwise; and ii) contracted, zero otherwise (based on the same definition as in Figures 3 and 4). Third, we test if the strength of the productivity-reallocation link changes following the onset of the pandemic by incorporating data from 2019 (which creates a time series dimension) and then include an interaction term between LP and a dummy variable equal to 1 if year=2020. The model is based on a more restricted sample of firms (i.e. firms that are consistently observed since 2018) and controls for potential differences in the nature of shocks in 2019 and 2020, via the inclusion of location*industry*size*year FE (group 2).

40. In the context of this structure, we introduce some novel variables to shed more light on the nature of firm's adjustment to the COVID-19 shock. First, given the potential for labour market adjustment to take place on the intensive – as well as the extensive – margin, we re-estimate Equation [1] with the change in firm's hours worked as the dependent variable (Section 4.3). Second, we explore whether there is a role for technology in explaining workforce adjustments – above and beyond firm labour productivity – by introducing a tech-savvy dummy that equals 1 if a firm has more than 5 apps connected before the pandemic (Section 4.4).

[17] While labour productivity is often measured as value-added per worker, we adopt a turnover-based measure due to lack of data on intermediate inputs. A clear advantage of the turnover-based measure is that it allows for the inclusion of the small – but non-trivial – share of firms that record negative value-added, which are necessarily dropped when taking the logarithm of value-added per worker. Moreover, some studies utilise multi-factor productivity (MFP) but this is not possible to estimate due to the lack of information on capital stocks. Existing studies demonstrate that estimation results of Equation [1] are insensitive to the choice of productivity measure, reflecting the high correlation within industries between firm-level labour productivity and MFP (Decker et al., 2018) and turnover and value-added based labour productivity (Andrews and Hansell, 2021).

[18] We estimate this model on pooled cross-country data – with country and year interactions – and separately for each country.

4.2. Baseline econometric results

41. Table 1 shows estimates from regressions of the cumulative log change in firm-level employment between February 2020 and: *i*) February 2021 (Panel A); and *ii*) May 2020 (Panel B) on firm-level labour productivity in 2019. The coefficient on productivity in Column 1 is positive and statistically significant at the 1% level, suggesting that on average (within industries), high productivity firms were more likely to expand and low productivity firms were more likely to contract over the course of 2020.

42. Over the year to February 2021, the implied difference in employment growth between a high productivity firm – i.e. one with labour productivity (LP) one standard deviation above the industry mean – and a low productivity firm – i.e. one with LP one standard deviation below the industry mean – was 6.8 percentage points. This is especially true over the initial months of the pandemic, with the coefficient estimate in Column 5 roughly 20% higher than the coefficient in Column 1, which as discussed below reflects the asymmetric sectoral impact of the pandemic. Thus, reallocation remained productivity-enhancing, despite the onset of the pandemic and crisis phase policies that prioritised preservation over reallocation. Put differently, high productivity firms were more resilient to the COVID-19 shock, thus helping to minimise the potential scarring effects that an indiscriminate shakeout of productive firms – and the associated destruction of firm-specific intangible capital – would otherwise entail.

Table 1. Firm-level employment growth responsiveness to lagged productivity since the pandemic

Dependent variable: log change in firm-level employment since February 2020

February 2020 to:	A: February 2021			B: May 2020		
	(1)	(2)	(3)	(4)	(5)	(6)
Productivity	0.0423*** (0.00190)	0.0416*** (0.00199)	0.0410*** (0.00217)	0.0520*** (0.00324)	0.0488*** (0.00341)	0.0609*** (0.00446)
Productivity x Hard-hit industries		0.00696 (0.00592)			0.0340*** (0.00699)	
Productivity x New Zealand			-0.00456 (0.00608)			-0.0444*** (0.00584)
Productivity x United Kingdom			0.0129** (0.00501)			-0.0380*** (0.00522)
Fixed effects						
Ind, Reg, Cty, Size	YES	YES	YES	YES	YES	YES
Observations	148977	148977	148977	163139	163139	163139
Adj R2	0.060	0.060	0.060	0.159	0.159	0.16

Note: The table shows the baseline coefficient estimates from Equation 1, using pooled cross-country data. Hard hit industries include accommodation & food services, arts & recreation services and other services
Source: Authors calculation based on Xero SBI.

43. Between February and May 2020, noticeable differences emerge across industries and countries (Table 1, Panel B). Column 5 shows that the reallocation-productivity link was initially much stronger in industries hard-hit by the pandemic, suggesting that employment adjustments were disproportionately concentrated in lower productivity firms in industries centred on in-person services, such as Hospitality and Arts & Recreation. The "hard-hit" interaction term is statistically insignificant in Column 2, however, suggesting these sources of cross-industry heterogeneity narrowed significantly over the second half of 2020. Digging deeper, the "hard-hit" interaction is positive and statistically significant for Australia until at least August 2020, while the same is true for the United Kingdom until June 2020 (Table B.2 of Annex B).

But this term is insignificant for New Zealand, suggesting hard-hit industries behaved no differently to the rest of the economy.[19]

44. The negative interaction terms in Column 6 suggest that employment reallocation between February and May 2020 was less productivity-enhancing in New Zealand and the United Kingdom, compared to Australia. The implied difference in employment growth between a high productivity firm – i.e. one with labour productivity (LP) one standard deviation above the industry mean – and a low productivity firm – i.e. one with LP one standard deviation below the industry mean – is 9.8 percentage points in Australia, 2.7 percentage points in New Zealand and 3.8 percentage points in the United Kingdom. Over the year to February 2021, however, the difference in the productivity-reallocation link between Australia and New Zealand is no longer statistically significant (Column 3). Moreover, the United Kingdom now exhibits the strongest productivity-enhancing reallocation, with the employment growth differential between a high and low productivity firm rising to 8.9 percentage points (compared to 6.6 percentage points in Australia).

45. Table B.4 of Annex B shows that higher productivity firms are both more likely to add workers (Panel A) and less likely to shed workers (Panel B), although the productivity coefficient is larger in the contraction model. Firms in the lowest productivity quartile were 11.2 percentage points more likely to contract than the most productive quartile between February and May 2020 and this differential narrows to 8.7 percentage points over the year to February 2021 (Figure A.4 of Annex A). By contrast, firms in the most productive quartiles were 3.7 and 5.3 percentage points more likely to expand than the least productivity quartile over the corresponding periods. While these differences are material, it is significant that a non-trivial share of firms were still expanding and that these were disproportionately the most productive firms. Thus, productivity was a key ingredient in small business resilience to the pandemic.

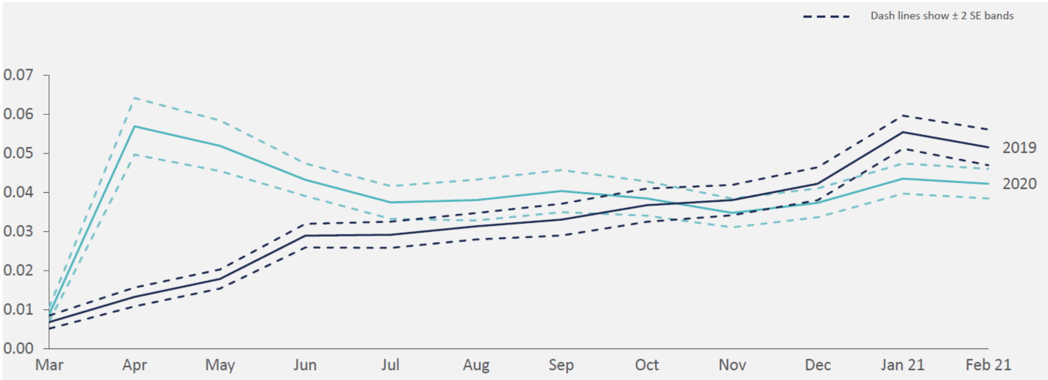
46. Next, we incorporate firm-level employment data from 2019 – and productivity data from 2018 – to explore whether the pandemic materially altered the nature of productivity-enhancing reallocation. Figure 6 Panel A compares the estimated productivity coefficient from the baseline model in Table 1 with estimated productivity coefficient from a model of cumulative employment growth from February 2019 to each month over the next year. This exercise suggests that on average across countries, the extent of productivity-enhancing reallocation accelerates over the first half of 2020, relative to the same period in 2019.

47. While this pattern is consistent with the cleansing hypothesis (see Section 2), significant cross-country differences emerge in the months following the onset of the pandemic. Many of these differences, however, are temporary and disappear by the December quarter 2020. Relative to 2019, the pandemic triggers an acceleration in productivity-enhancing reallocation in Australia and the United Kingdom: the implied difference in employment growth between a high and low productivity firm rises noticeably in Australia and the United Kingdom from February to September 2020 (Figure 6, Panel B). By contrast, productivity-enhancing reallocation declines in New Zealand following the pandemic, with this employment growth differential – between high and low productivity firms – declining by more than half, compared to before the pandemic. That said, it is notable that firm-level employment changes are more strongly connected to productivity in New Zealand before the pandemic, than in Australia and the United Kingdom.

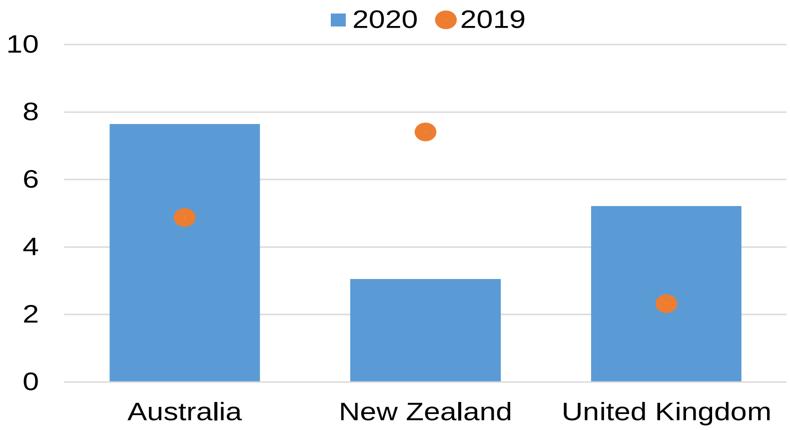
[19] The results for Australia may reflect the fact that the job retention scheme did not cover short-tenure casual workers, who were more likely to work in hospitality, while workforce coverage of New Zealand's job retention scheme was much more broad-based. See Section 5 for more discussion.

Figure 6. Productivity-enhancing reallocation accelerates over the first half of 2020

A: Estimated responsiveness of employment change since February (2020 or 2019) to productivity



B: Implied difference in employment growth (February to September) between a high and low productivity firm



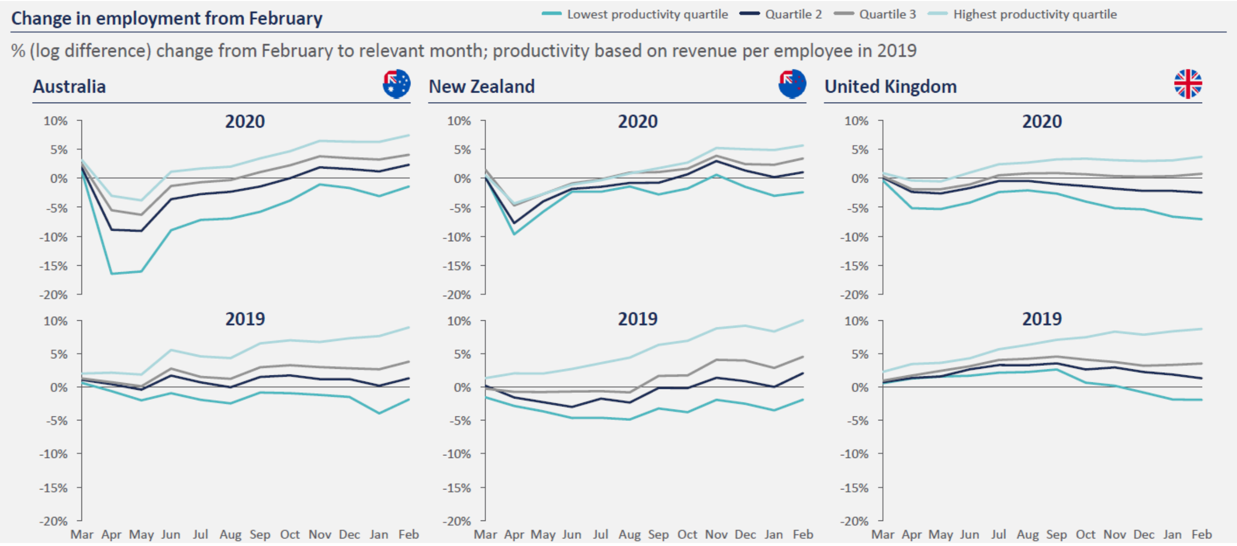
Note: Based on the coefficient estimates for Equation 1, which controls for a range of confounding factors from separate country regressions in Annex B. Panel B applies the coefficient estimates in Table B.1 of Annex B, to the country-specific (average within-industry) standard deviations of labour productivity for 2018 and 2019.
Source: Authors calculation based on Xero SBI.

48. Another way to visualise the impact of pandemic on productivity-enhancing reallocation dynamics is to track the evolution of firm-level employment across the (pre-crisis) labour productivity quartiles. Figure 7 plots the estimated coefficients for each productivity quartile – from a model which contains the identical control variables to the baseline – which reveal economically and statistically significant differences in employment performance between firms in the most and least productive quartiles.

49. This alternate approach confirms the cross-country patterns identified above. First, larger differences in employment performance between top and bottom productivity quartiles are evident in Australia over the first half 2020, compared to the same period in 2019. Put differently, the most productive quartile of firms are more resilient to the shock in Australia while this also appears to be the case in United Kingdom. Second, employment growth differences between the most and least productive quartiles clearly narrows in New Zealand following the onset of the pandemic, compared to 2019. This is consistent with the larger decline in job reallocation in New Zealand in the initial months following the onset of the pandemic, as reflected in an employment growth distribution that features an increasing share of static firms (Figure 3).

Figure 7. Evolution of firm-level employment by labour productivity quartile

Estimated log change in employment since February, purged of correlates



Note: Based on the coefficient estimates presented in Table B.3 of Annex B, from a model that controls for a battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

4.3. Adjustment on the hours worked margin

50. These patterns in workforce adjustment following the onset of the pandemic are also evident when we focus on hour worked. First, we re-estimate the baseline model (see Equation 1) and relate the change in hours worked since February 2020 – as opposed to the heads measure – to firm-level labour productivity. Focusing on Table 2 Panel B, the estimated coefficient on productivity in Columns 1, is positive and significant, suggesting on average across countries, low (high) productivity firms were more (less) likely to reduce hours worked since the onset of the pandemic. This is especially the case between February and May 2020, with the coefficient on productivity in Column 4 more than twice as large as in Column 1.

Table 2. Productivity and reallocation since the pandemic: the role of hours worked and technology

A: log change in firm-level employment since February 2020

February 2020 to:		**A: February 2021**			**B: May 2020**	
	(1)	(2)	(3)	(4)	(5)	(6)
Productivity	0.0423*** (0.0019)		0.0417*** (0.00181)	0.0520*** (0.00324)		0.0518*** (0.00323)
High-tech dummy		0.0302*** (0.00378)	0.0207*** (0.00372)		0.0216*** (0.00326)	0.0098*** (0.00300)
Fixed effects						
Ind, Reg, Cty, Size	YES	YES	YES	YES	YES	YES
Observations	148977	148977	148977	163139	163139	163139
Adj R2	0.060	0.055	0.060	0.159	0.146	0.159

B: change in hours worked since February 2020

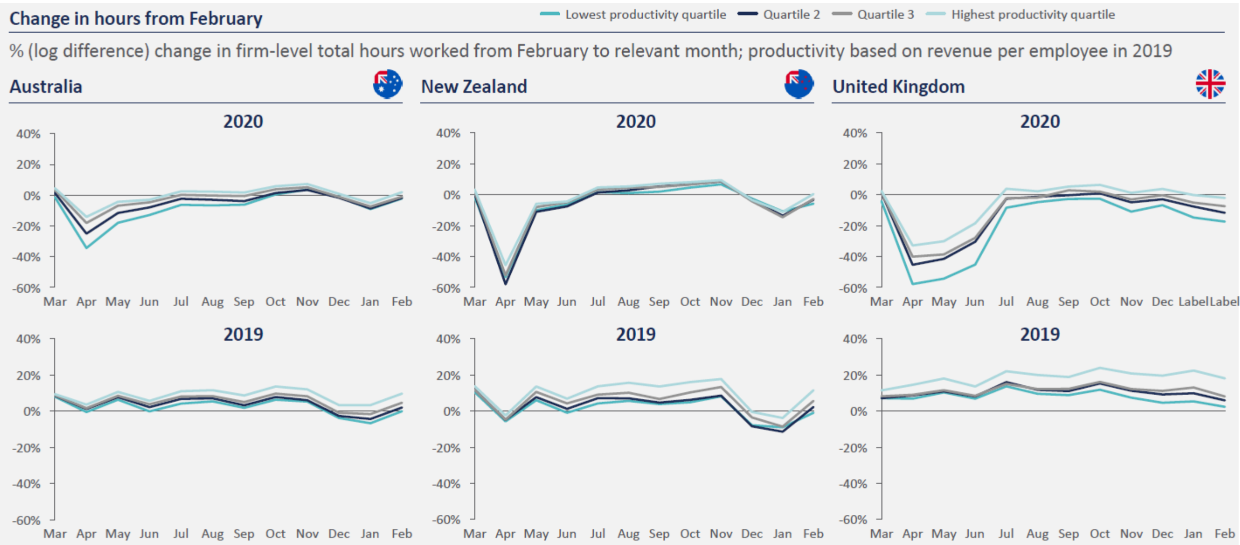
February 2020 to:	A: February 2021			B: May 2020		
	(1)	(2)	(3)	(4)	(5)	(6)
Productivity	0.0244*** (0.00272)		0.0237*** (0.00274)	0.0689*** (0.00485)		0.0685*** (0.00482)
High-tech dummy		0.0288*** (0.00542)	0.0232*** (0.00544)		0.0289*** (0.00629)	0.0132** (0.00593)
Fixed effects						
Ind, Reg, Cty, Size	YES	YES	YES	YES	YES	YES
Observations	139248	139248	139248	146965	146965	146965
Adj R2	0.043	0.042	0.043	0.132	0.126	0.132

Note: The table augments the baseline model estimates in Table 1, by including a High-tech dummy (equals one if a firm has 5 or more apps connected in February 2020; zero otherwise) and replacing employment with hours worked as the dependent variable in Panel B.
Source: Authors calculation based on Xero SBI.

51. Second, to explore cross-country differences, Figure 8 charts the estimated change in hours worked for each quartile of firm-level labour productivity, using a similar methodology to that in Figure 7. In Australia and the United Kingdom, the decline in hours worked is particularly sharp in the least productive quartile of firms over the initial months and there is some evidence that changes in hours worked are more strongly connected to productivity relative to the same period in 2019. By contrast, the differences are less marked in New Zealand, and if anything, the gap in hours worked between the top and bottom productivity quartile are larger in 2019. Taken together, these results are consistent with the cross-country differences in productivity-enhancing labour reallocation based on total employment presented in Section 4.2.

Figure 8. Evolution of firm-level hours worked by labour productivity quartile

Estimated log change in hours worked since February, purged of correlates



Note: Based on the coefficient estimates presented in Table B.5 of Annex B, from a model that controls for a battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

4.4. Role of technology usage

52. As mentioned in Section 3, it is also possible to explore how employment changes following the onset of the pandemic varied with a firm's App usage. This is clearly of interest, given that the pandemic accelerated the shift in activity towards online marketplaces, which helped to sustain production in the face of severe disruptions to traditional economic activities.

53. Unsurprisingly, Figure A.5 of Annex A shows that there is a positive correlation between labour productivity and App usage within country-industry cells, both in terms of the probability of adoption (Panel A) and intensity of App usage (Panel B). While high productivity firms are more likely to employ Apps, that App usage remains significant amongst firms in the lower productivity quartiles implies that it may contain some information about the fundamentals of the firm, over and above labour productivity. App usage could be a sign that firms are making significant intangible investments, which will only crystalize a market return – and thus be reflected in higher labour productivity – in the future. This might especially apply to young businesses that are still undergoing a process learning-by-doing and technological experimentation such that they may appear unproductive in the short run, but have the potential to reveal high productivity in the future (Ouyang 2009). This implies that for a given labour productivity level, firms with higher App usage may have higher organisational and technological capability, which could enhance their resilience to the pandemic. App usage may also be more reflective of total factor productivity than labour productivity.

54. Table 2 Panel A presents estimates of a baseline equation that includes a "High-tech" dummy variable that equals one if a firm had five or more apps connected before the pandemic (based on the intensity measure in Panel B, Figure A.5). The results are broadly consistent with the idea that tech-savvy firms were more resilient to the pandemic. Between February and May 2020, employment growth in tech-savvy firms was 2.2 percentage points higher than other firms (Column 5), with this differential reaching 3 percentage points by February 2021 (Column 2). This effect remains even after controlling for firm-level labour productivity, although the employment growth differential is more modest (Columns 3 and 6).[20]

55. The coefficients estimates (in Column 3) imply that over the year to February 2021, for example, employment growth in tech-savvy firms was 2.1 percentage points higher than other firms. This compares to an employment growth gap of 6.7 percentage points between a high productivity firm and a low productivity firm (defined as firms one standard deviation above/below the industry productivity mean).The larger economic magnitude of the productivity term (compared to the High-tech dummy) is unsurprising, given that labour productivity more broadly captures firm capability than App usage. Even so, firms that use Apps more intensively are more likely to increase hours than other firms (Panel B) and the magnitude of the "High Tech" dummy is comparable to the productivity coefficient.

56. While these results are consistent with the idea that "higher tech" firms were more resilient to the pandemic – even after controlling for productivity – an alternate explanation is that app usage is endogenous to growth expectations. If firms expect to expand in the future, they may make pre-emptive investments in cashflow reporting and management apps so that they can more effectively manage a larger workforce when it materialises. This hypothesis cannot be rejected on the evidence at hand. For example, high-tech firms are more likely to expand than other firms but they are no less likely to contract (see Table B.6 of Annex B). While this is consistent with app usage being endogenous to growth expectations, it could also suggest that high-tech firms were more able to nimbly adjust to rapidly changing market conditions and seize new growth opportunities – for example, related to online sales – induced by the pandemic. It may also suggest that young firms' fragile learning-by-doing process was not overly disrupted by the pandemic (Ouyang 2009) although more research is required to pin down this channel. Regardless of the mechanism, the app usage variable contains a clear economic signal and warrants further research.

[20] We also included an interaction between Productivity and High-tech but this was not significant.

4.5. Robustness

57. We conducted a range of robustness tests to the baseline results. For example:

- The cross-country estimates of the reallocation-productivity link are broadly similar if we re-estimate the baseline chart (Figure 6, Panel A) for a balanced panel of firms we observe in both 2019 and 2020 (see Figure A.6 of Annex A and Table B.7 of Annex B).
- The evolution of employment across the quartiles of firm-level labour productivity (in Figure 7) is very similar for Australia and New Zealand when we redefine jobs in terms of having worked for more than one hour, as opposed to have been paid (see Figure A.7 of Annex A).
    - Unsurprisingly, this metric yields more dramatic declines in employment in the United Kingdom – consistent with the design of the UK's job retention scheme, which "furloughed" workers (i.e. temporarily placed on zero hours) – but firm-level labour adjustments remain strongly linked to productivity (Figure A.7).
- Excluding firm size fixed effects results in a larger coefficient on labour productivity (Table B.8). This is unsurprising given the: *i*) strong covariance between productivity and firm size (Andrews and Cingano, 2014; Andrews and Hansell, 2021); and ii) pandemic hit smaller firms harder.
- Finally, the results in Table 2 are broadly robust to defining high tech firms in terms of having at least one app connected, as opposed to having at least five apps connected (Table B.9).

5. Productivity, reallocation and job retention schemes

58. Why did workforce adjustments remain connected to productivity at the firm-level, despite a crisis policy response – via job retention schemes – that prioritised preservation over reallocation? To make progress on this question, we leverage Xero's unique information on worker tenure and employment arrangements to explore the implications for productivity-enhancing dynamics of Australia's JobKeeper scheme.

59. In late March, the Australian government introduced a wage subsidy scheme, JobKeeper, to combat the labour market shock. Broadly speaking, firms could receive a $1500 per fortnight subsidy per employee if they met two criteria: *i*) the firm had to *expect* a decline in turnover of at least 30%; and *ii*) the worker must be either permanently employed by the firm, or have been with the firm at least 12 months and working regular hours.[21] The second criteria meant that short-tenure casual workers were ineligible for the JobKeeper subsidy. The latter effectively created cross-firm variation in eligibility for the JobKeeper payment in accordance with a firm's (pre-pandemic) workforce characteristics, conditional on the first criteria being met.[22]

60. Figure 9 shows the change in employment (Panel A) and hours worked (Panel B) since the onset of the pandemic for two groups of workers – those eligible and ineligible for the JobKeeper scheme – according to the (within-industry) productivity quartile of their firm. As before, the chart utilises regression coefficients from a model that carefully controls for a range of potential correlates (see Section 4.1). Two key points emerge. First, job losses were disproportionately concentrated among ineligible employees, consistent with Australian Treasury (2020). This partly reflects the effect of the policy on retention: Bishop

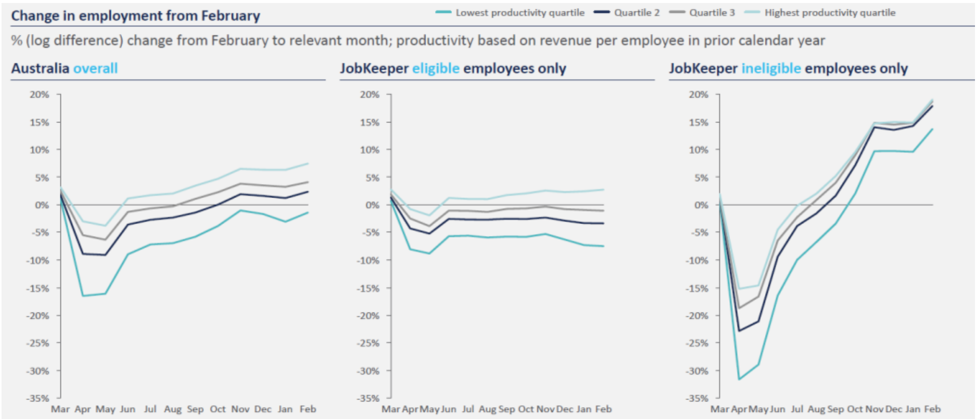
[21] Australia has an employment classification called "casual"; these employees have no guaranteed hours, no annual or sick leave, and the employment relationship can be terminated by either party on short notice. To compensate, these employees receive a mandatory "loading" in higher wages above their permanent employee counterparts. This loading can vary depending on the employee's occupation and industry, but is typically 25%.

[22] However, such workers could draw income support from (significantly higher) unemployment benefits in the event that their employment relationship was dissolved during the pandemic.

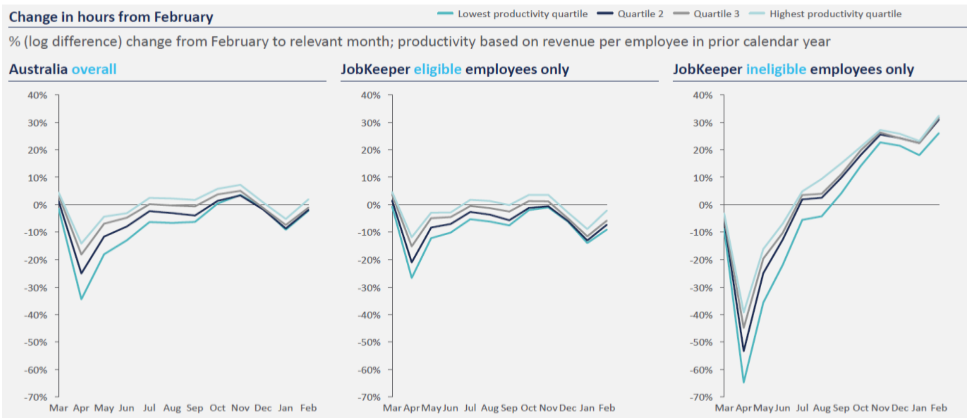
and Day (2020) estimated that the JobKeeper Payment increased the likelihood of a JobKeeper-nominated employee remaining employed over the April to July 2020 period by around 20 per cent, potentially saving at least 700,000 jobs at the height of the crisis. But this pattern may also reflect that short-term casual employees are, by definition, less tightly connected to their firm and likely have a lower value job match. As such, they may represent the key margin for firm downsizing in the face of an adverse shock, implying that they would have likely experienced larger job losses even in the absence of JobKeeper scheme.

Figure 9. Productivity-enhancing reallocation and the JobKeeper Scheme

A: Estimated log change in employment since February 2020, purged of correlates



B: Estimated change in hours worked since February 2020, purged of correlates



Note: The figure shows how the estimated average employment growth across each (within-industry) labour productivity quartile since the onset of the pandemic for three pools of workers: all workers, and those potentially eligible for JobKeeper and ineligible for JobKeeper as defined based on pre-pandemic work arrangements. It is based on the same econometric approach underlying Figures 7 and 8. Underlying regression estimates are available from the authors on request.
Source: Authors calculation based on Xero SBI.

61. Second, reallocation was productivity-enhancing amongst both groups of workers, although it was most stark among the class of employees ineligible for JobKeeper.[23] Between February and April 2020, firms in the highest productivity quartile shed an estimated 0.8% of their eligible employees, compared to an estimated loss of 8.1% for the least productive firms. But firms in the highest productivity quartile lost

[23] We do not consider the firm-level eligibility threshold (given it relied on firm expectations, and so was fuzzy); this means not all eligible employees will have been at eligible firms.

15.2% of ineligible employees, compared to 31.6% among firms in the lowest productivity quartiles. Similar patterns also emerge with respect to hours worked (Figure 9, Panel B).

62. Table 3 explores how productivity-enhancing reallocation changed following the onset of the pandemic, for the two pools of workers. The odd (even) numbered columns models the change in employment between February and May (September) during 2019 and 2020. We do not look beyond September, given changes to the design of the JobKeeper scheme that took effect from the end of September 2020. Across JobKeeper eligible (Panel A) and ineligible (Panel B) workers, the pace of productivity-enhancing reallocation accelerated following the onset of the pandemic, as indicated by the positive *Productivity x 2020* term. The extent of this pick-up, however, is proportionately larger amongst the pool of ineligible workers, with an implied difference in employment growth between a high and low productivity firm rising to 7.2 percentage points in 2020, compared to 3.2 percentage points in 2019 (over the February to September period; Column 3).[24] Amongst the pool of JobKeeper eligible workers, the corresponding differential rose more modestly, from 6.7 percentage points in 2019 to 7.7 percentage points in 2020.

Table 3. Productivity-enhancing labour reallocation in Australia: the role of JobKeeper

Log change in firm-level employment since February to subsequent months; 2019 and 2020

	A: JobKeeper eligible workers		B: JobKeeper ineligible workers	
February to:	May	September	May	September
	(1)	(2)	(3)	(4)
Productivity	0.0200*** (0.00120)	0.0413*** (0.00173)	0.0106*** (0.00539)	0.0199*** (0.00639)
Productivity x 2020	0.0233*** (0.00329)	0.00604* (0.00317)	0.0894*** (0.0142)	0.0247* (0.0131)
Fixed effects				
Ind, Reg, Size, Year	YES	YES	YES	YES
Observations	165182	161994	32452	35926
Adj R2	0.085	0.065	0.237	0.122

Note: The table shows how the relationship between employment growth – measured over February and May (odd columns) and February and September (even columns) – and firm-level productivity changed between 2019 and 2020, for two pools of workers – those potentially eligible for JobKeeper (Panel A) and ineligible for JobKeeper (Panel B) – that are defined based on pre-pandemic work arrangements.
Source: Authors calculation based on Xero SBI.

63. Evidence of stronger productivity-enhancing reallocation amongst the pool of workers ineligible for JobKeeper is consistent with the cleansing dynamics that may characterise unfettered markets in the face of an adverse shock (see Section 2). At first glance, this may be consistent with the idea that job retention schemes stymie productivity-enhancing reallocation, particularly when viewed in conjunction with the differences between Australia and New Zealand identified above. But causality is difficult to establish, given that short-tenure casuals (i.e. ineligible workers) are likely the key margin for firm downsizing in the face of an adverse shock regardless of the policy response. Moreover, that the reallocation-productivity link remained intact amongst the JobKeeper eligible workforce suggests that the JRS did not completely distort natural market selection. This is significant given concerns that JRS could risk zombification by overly protecting low productivity firms and potentially crowd-out growth opportunities for more productive firms.

[24] As in Section 4, a high (low) productivity firm is defined as a business with labour productivity one standard deviation above (below) the industry mean.

64. Future research could leverage Xero SBI data to develop precise metrics of firms' actual take-up of the scheme, and in turn analyse the characteristics of firms that participated in JobKeeper. One possible explanation for why JobKeeper did not completely distort the productivity-reallocation link is that higher productivity firms were more likely to participate in JobKeeper. Andrews, Bahar and Hambur (2021) present a range of evidence in favour of this hypothesis – based on analysis that merges Single Touch Payroll with Business Income Taxation data from the Australian Tax Office – particularly for the first phase of the JobKeeper scheme.[25] While somewhat surprising, these result are consistent with canonical models of firm dynamics such as Hopenhayn (1992) and Jovanovic (1982). When faced by uncertain future outcomes – and some fixed costs of operation – higher productivity firms are more likely to take on the cost and operate, given the higher expected value of doing so. Thus, more productive firms may have been more likely to select into the JobKeeper scheme, against a backdrop of pandemic-induced uncertainty. This non-random selection raises the prospect that JobKeeper disproportionately subsidised *higher* productivity firms, thereby shielding them from the shock.

65. Scope for equivalent case studies for New Zealand and the United Kingdom is limited, partly due to the broader coverage of their wage subsidy schemes. Nevertheless, the temporary acceleration in productivity-enhancing reallocation dynamics in Australia – compared to the United Kingdom and particularly New Zealand – could plausibly stem from the later introduction and unique design features of the JobKeeper scheme. This meant that policy-induced hibernation was less complete in Australia, which resulted in employment contraction that was more strongly concentrated in lower productivity firms. By contrast, New Zealand's job retention scheme protected a greater share of the workforce (Figure A.3, Annex A), which left less scope for the cleansing dynamics observed in Australia.

66. Finally, these potential impacts of job retention schemes on reallocation should not be viewed in isolation. Instead, they should be assessed against the broader aims of such schemes, which included supporting household incomes, reducing uncertainty and temporarily shielding firm-specific capital (by maintaining the connection between workers and firms) in the face of arguably the largest macroeconomic shock since the Great Depression.

6. Conclusion

67. The consequences of the pandemic for potential output will partly hinge on its impact on productive smaller firms, and more generally the ongoing process of productivity-enhancing reallocation – the rate at which scarce resources are reallocated from less productive to more productive firms. While Schumpeter (1939) originally proposed that recessions can accelerate this process, the more 'random' nature of the COVID-19 shock coupled with a policy response that prioritised preservation (over reallocation) raises questions about whether job reallocation remained productivity-enhancing over the course of the pandemic. In this paper, we use near-real-time data from Xero – a cloud accounting platform – to produce the first systematic cross-country evidence on this question.

68. Our results suggest that on average across countries, job reallocation remained firmly linked to productivity following the onset of the pandemic. While this differential reflects the strong tendency for job

[25] On average across industries in Xero SBI, while less than two-thirds of employees working in firms in the lowest productivity quartile were eligible for JobKeeper, the most productive quartile of firms had over 85% of their workforce eligible. This is consistent with the idea that high productivity firms are better managed (Bloom and Van Reenen, 2007), which enables them to more effectively recruit and retain talented staff. Overall, this results in higher firm-worker match quality and lower employee turnover, and thus more long-term employees eligible for JobKeeper. But it could also reflect a mechanical effect, whereby greater reliance on short-tenure casuals raises workforce turnover, which in turn depresses labour productivity when measured on a heads basis (i.e. sales per worker). Andrews, Bahar and Hambur (2021) present a range of tests to show that this mechanical effect is not driving their results but further work is required using the Xero data.

losses to be concentrated in the least productive quartile of firms, high productivity firms were also more likely to expand their workforce over the course of the pandemic. Furthermore, the reallocation-productivity link temporarily strengthened over the first half of 2020 – relative to same period in 2019 –partly driven by industries centred on in-person services – e.g. Hospitality and Arts & Recreation – that were particularly hard-hit by the pandemic. These patterns are broadly consistent with Schumpeter's cleansing hypothesis, which predicts that the reallocation-productivity link to strengthen with the size of the recessionary impulse. We also show that the link between workforce adjustments and productivity is also evident in hours worked at the firm level – a novel variable in the Xero database.

69. Cross-country differences emerge in the pandemic's impact on job reallocation and productivity. The temporary surge in the reallocation-productivity link over the first half of 2020 is largely driven by Australia. By contrast, the onset of the pandemic in New Zealand is associated with a weakening of reallocation-productivity link. We document a more extensive "hibernation" of the New Zealand economy over the initial months of the pandemic, as reflected in a sharp increase in the prevalence of static firms, whereas firm contraction was more common in Australia. These patterns may partly reflect the earlier introduction of New Zealand's job retention scheme, which also protected a greater share of the workforce than in Australia. But these cross-country differences should not be overplayed as they had largely faded by late 2020. In fact, over the year to February 2021, the extent of productivity-enhancing reallocation is strongest in the United Kingdom, consistent with the greater severity of the macroeconomic shock.

70. Productivity was a key ingredient of small business resilience to the pandemic. This is consistent with the idea that COVID-19 accentuated the importance of firm capabilities and organisational capital by forcing a wave of business experimentation and accelerated digital transformation (Barrero et al 2020). High productivity firms – due to their superior managerial practices (Bloom and Van Reenen, 2007) – could more effectively adjust to changing market conditions. But we find that technology adoption also played a role, with jobs and hours worked holding up more amongst firms that intensively use apps to manage their business, even after controlling for productivity. App usage may reflect a budding organisational and technological capability – which although not yet fully reflected in productivity – could have helped them to capitalise on new growth opportunities induced by the pandemic. Indeed, while policy partly suppressed the rate of creative destruction, the nature of the shock – i.e. one where being online and able to operate remotely – played to the strengths of high productivity and tech-savvy firms. Thus, we observed a reallocation of labour to such firms, despite a policy response that emphasised preservation over reallocation. The greater resilience of high productivity and tech-savvy firms is significant, given that an indiscriminate shakeout of such firms would have imparted lasting scars on the productive and social fabric.

71. Finally, we document a pronounced acceleration in productivity-enhancing reallocation dynamics following the onset of the pandemic amongst the pool of workers potentially ineligible for the JobKeeper subsidy. Underlying this is a sharp employment contraction amongst the lowest productivity quartile, which is consistent the cleansing dynamics that may characterise unfettered markets in the face of a very large adverse shock. But we also find that productivity-enhancing reallocation intensified amongst the pool of eligible workers. While this finding is surprising, it is consistent with evidence that higher productivity firms were more likely to participate in the initial phase of the JobKeeper scheme (Andrews, Bahar and Hambur, 2021). This raises the prospect that JobKeeper disproportionately shielded *higher* productivity firms from the shock – a topic that future research could investigate in the context of Xero SBI.

72. Indeed, our research represents only the tip of the iceberg and Xero SBI could shed light on other aspects of firm dynamics and productivity. While this paper focused on how employment adjustments since the pandemic were connected to pre-crisis labour productivity, there are reasons to suspect that the pandemic may affect within-firm labour productivity. In this regard, future analysis could explore the extent to which the pandemic accelerated digital adoption within firms, and the associated implications for productivity growth. Such research can help shed light on the longer-run consequences of short-run shocks in a more timely fashion, thereby helping policy makers and business leaders to make more informed decisions.

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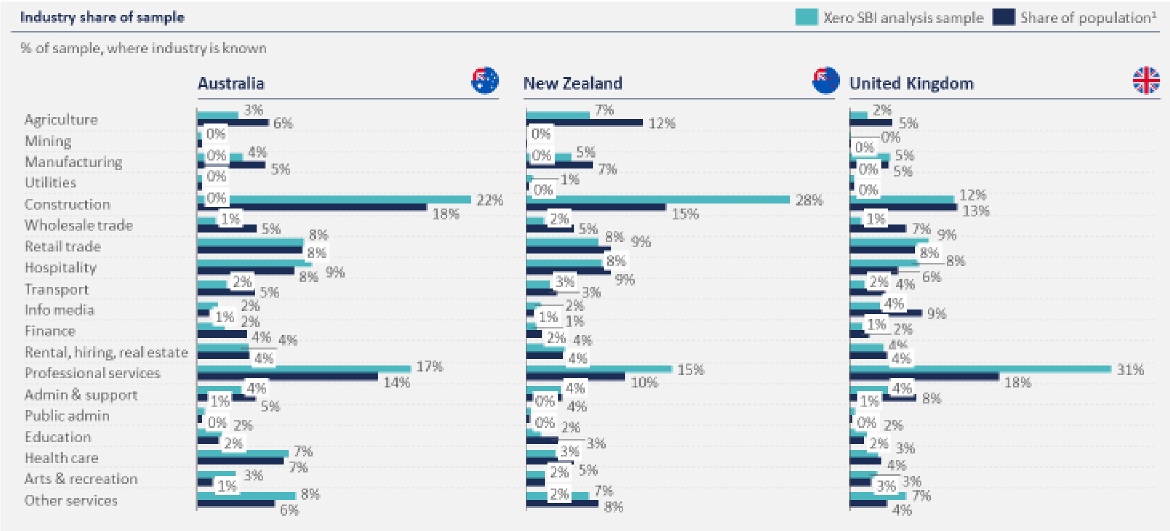
Annex A. Additional figures

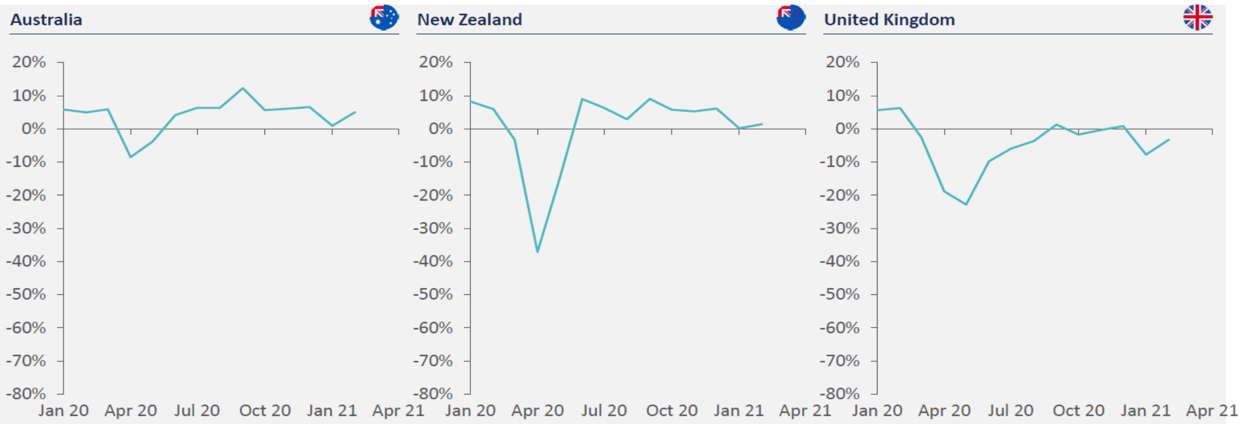
Figure A.1. Distribution of firms by industry



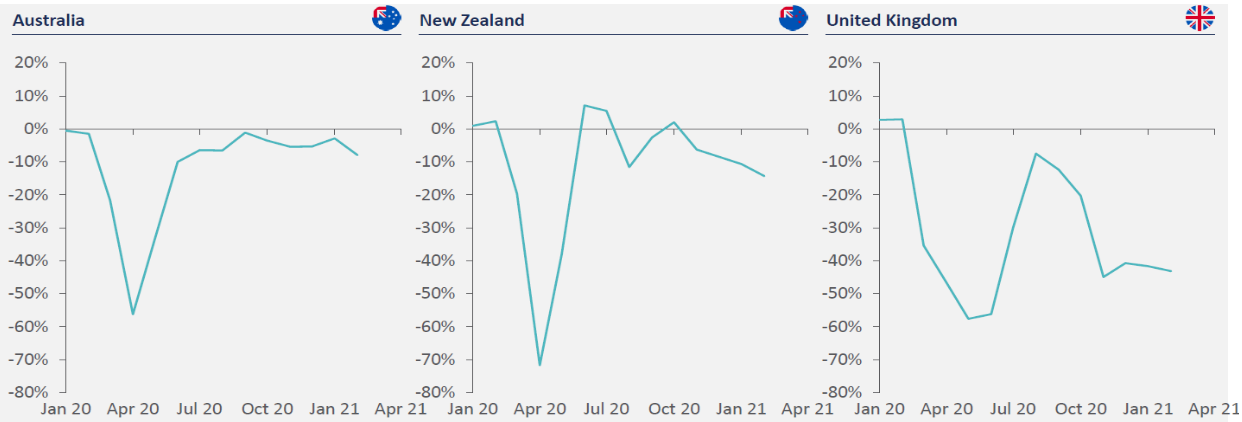
Note: The figure compares the distribution of firms by industry in the subset of the Xero SBI data that we use to official sources for each country. Industry classification is self-reported by Xero subscribers. (1) Population sources are Australia: ABS (FY 2018/19); New Zealand: StatsNZ (FY 2019); United Kingdom: ONS (FY 2019)
Source: Authors calculation based on Xero SBI and National Statistical Offices (ABS, StatsNZ and ONS).

Figure A.2. Average within-firm turnover (year-on-year) growth

A: All sectors



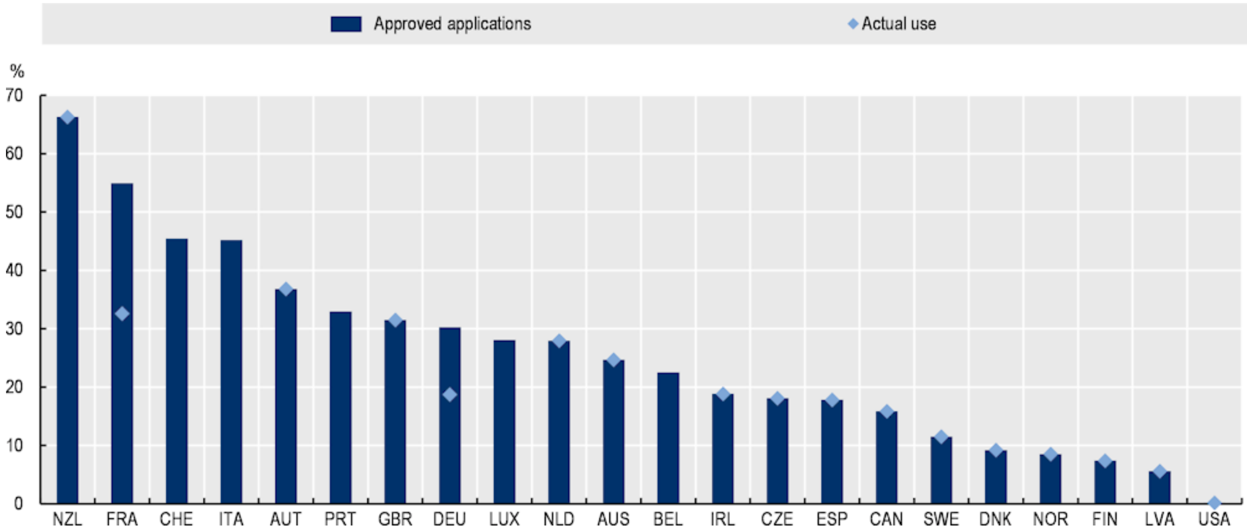
B: Hospitality



Note: The figures shows the average change in turnover growth within firms, relative to the same month a year earlier.
Source: Authors calculation based on Xero SBI.

Figure A.3. Participation in job retention schemes across OECD countries

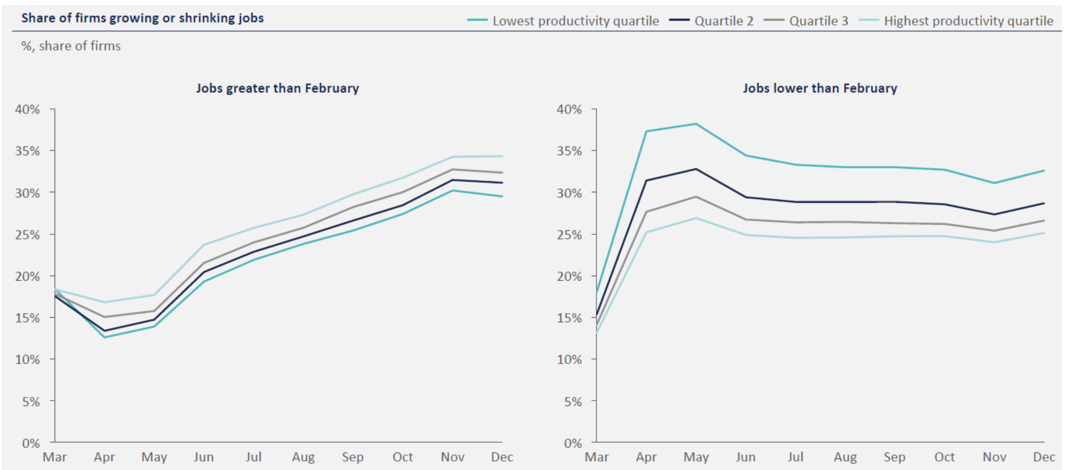
Share of dependent employees



Note: Take-up rates are calculated as a percentage of dependent employees in 2019 Q4. Data refer to end May except for Luxembourg and Switzerland (end April). Australia, Canada, Ireland, the Netherlands and New Zealand operate wage subsidy schemes, which are not conditional on the reduction in working hours. United States: data refer to participation in short-time compensation schemes.
Source: OECD (2020) based on National sources.

Figure A.4. Firm expansion and contraction across the productivity distribution

Estimated share of firms growing or shrinking (in terms of employment); purged of correlates

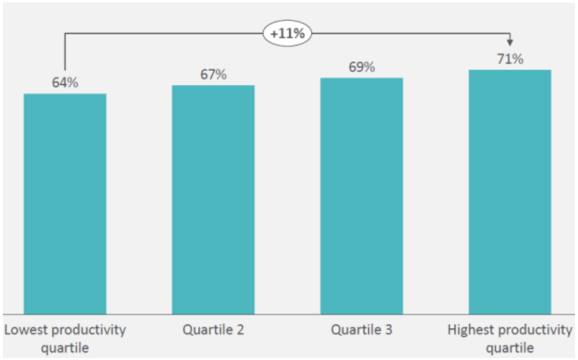


Note: Based on the coefficient estimates in Table B76.
Source: Authors calculation based on Xero SBI.

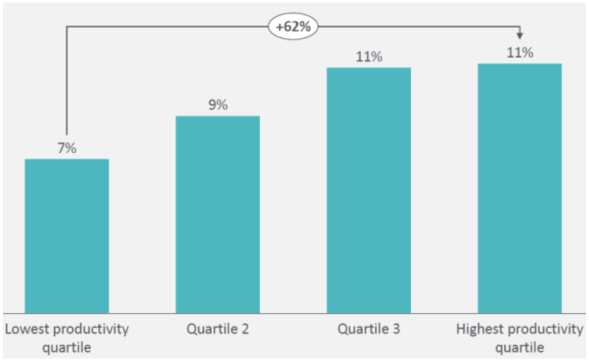
Figure A.5. High productivity firms are more tech-savvy

Use apps by productivity quartile; average of shares within country-industry cells

A: Share of firms with apps connected to their Xero account



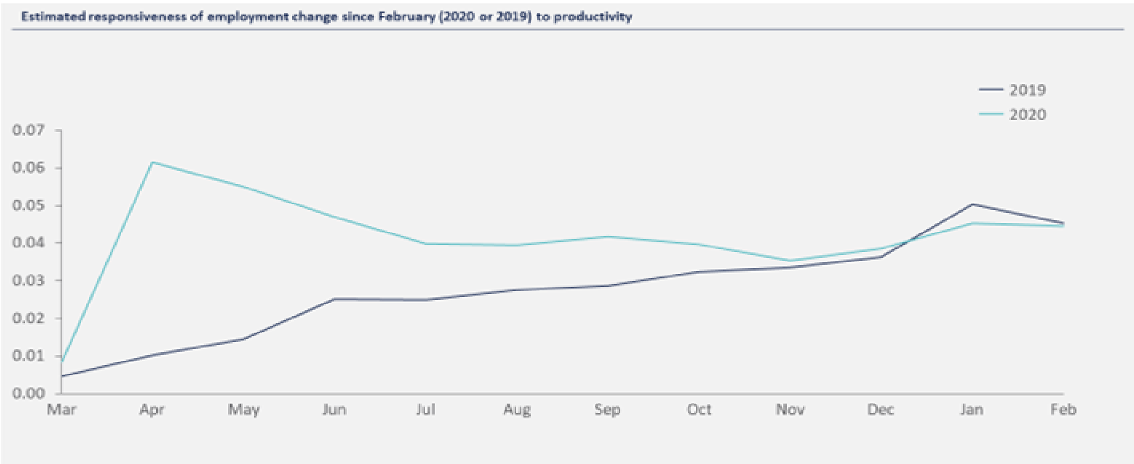
B: Share of firms with 5 or more apps connected to their Xero account



Note: The figure shows the average share of firms with apps connected to their Xero account by labour productivity quartile; average is within country by productivity quartiles.
Source: Authors calculation based on Xero SBI.

Figure A.6. Productivity-enhancing reallocation accelerates over the first half of 2020 – robustness

Estimated responsiveness of employment change since February (2020 or 2019) to productivity; balanced panel



Note: The figure shows the implied coefficient estimates from Table B7, based on the specification in Equation 1 that uses pooled cross-country data. In all cases, the models control for the battery of fixed effects outlined in Section 4.1. The sample is based on a balanced panel of firms, which we observe in both 2019 and 2020.
Source: Authors calculation based on Xero SBI.

Figure A.7. Evolution of firm-level employment by labour productivity quartile – alternative definition of jobs

Log change in employment since February 2020

Notes: The figures is based upon the estimated coefficient estimates for each productivity quartile, using the specification outlined in Section 4.1, which controls for a battery of fixed effects (see Table B5, Panel for more information). Employment is re-defined in terms of having worked for more than one hour, as opposed to have been paid (see Section 4.5).
Source: Authors calculation based on Xero SBI.

Annex B. Additional tables

Table B.1. Firm-level employment growth responsiveness to lagged productivity: country specific estimates

Log change in firm-level employment since February to various months (2020 or 2019)

	Australia				New Zealand				United Kingdom			
	February (next year)	December	September	May	February (next year)	December	September	May	February (next year)	December	September	May
Productivity	0.0445***	0.0358***	0.0296***	0.0148***	0.0520***	0.0470***	0.0402***	0.0239***	0.0467***	0.0318***	0.0133***	0.00545
	(0.00283)	(0.00249)	(0.00238)	(0.00138)	(0.00637)	(0.00656)	(0.00674)	(0.00523)	(0.00540)	(0.00486)	(0.00506)	(0.00335)
Productivity * 2020	-0.00154	0.00266	0.0165***	0.0485***	-0.0110	-0.0119	-0.0220**	-0.00490	0.0127	0.0105	0.0160**	0.0178***
	(0.00389)	(0.00363)	(0.00435)	(0.00508)	(0.00961)	(0.00932)	(0.00904)	(0.00712)	(0.00820)	(0.00722)	(0.00646)	(0.00478)
Constant	-0.493***	-0.423***	-0.446***	-0.514***	-0.531***	-0.469***	-0.344***	-0.279***	-0.590***	-0.407***	-0.216***	-0.161***
	(0.0234)	(0.0218)	(0.0262)	(0.0306)	(0.0578)	(0.0560)	(0.0543)	(0.0428)	(0.0462)	(0.0407)	(0.0363)	(0.0269)
N	159,504	164,494	168,368	171,164	17,462	17,630	18,026	18,694	21,434	21,438	22,094	22,620
R2	0.044	0.043	0.065	0.140	0.122	0.120	0.129	0.134	0.125	0.114	0.093	0.100

Notes: The tables show econometric estimates of Equation 1, on a country-by-country basis (i.e. not pooled data). In all cases, the models control for the battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

Table B.2. Firm-level employment growth responsiveness to lagged productivity: hard-hit industries – country specific estimates

Log change in firm-level employment since February to various months (2020 or 2019)

February 2020 to:	A: February 2021			B: May 2020		
	Australia	**New Zealand**	**United Kingdom**	**Australia**	**New Zealand**	**United Kingdom**
Productivity	0.0403*** (0.00226)	0.0362*** (0.00612)	0.0536*** (0.00483)	0.0573*** (0.00459)	0.0156*** (0.00390)	0.0211*** (0.00278)
Productivity x hard-hit industry	0.00773 (0.00678)	0.00337 (0.0184)	0.00308 (0.0151)	0.0375*** (0.00908)	0.0120 (0.0177)	0.0188* (0.00971)
Fixed effects						
Ind, Reg, Size	YES	YES	YES	YES	YES	YES
Observations	115,275	14,510	19,192	126,880	15,720	20,539
R2	0.047	0.095	0.117	0.166	0.110	0.082

Notes: The tables show econometric estimates of Equation 1, on a country-by-country basis (i.e. not pooled data). In all cases, the models control for the battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

Table B.3. Firm-level employment growth responsiveness to lagged productivity quartile

A: Log change in firm-level employment since February 2020

Australia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	March	April	May	June	July	August	September	October	November	December	January	February
Dummy (quartile = 2)	0.00647***	0.0762***	0.0702***	0.0537***	0.0448***	0.0463***	0.0437***	0.0386***	0.0295***	0.0329***	0.0427***	0.0375***
	(0.00170)	(0.00732)	(0.00671)	(0.00469)	(0.00419)	(0.00492)	(0.00517)	(0.00418)	(0.00393)	(0.00407)	(0.00423)	(0.00411)
Dummy (quartile = 3)	0.0136***	0.110***	0.0979***	0.0766***	0.0653***	0.0666***	0.0685***	0.0610***	0.0485***	0.0517***	0.0631***	0.0548***
	(0.00174)	(0.00912)	(0.00853)	(0.00522)	(0.00497)	(0.00600)	(0.00635)	(0.00513)	(0.00410)	(0.00403)	(0.00445)	(0.00392)
Dummy (quartile = 4)	0.0203***	0.135***	0.123***	0.101***	0.0891***	0.0899***	0.0923***	0.0852***	0.0754***	0.0800***	0.0936***	0.0886***
	(0.00205)	(0.00978)	(0.00870)	(0.00523)	(0.00522)	(0.00643)	(0.00657)	(0.00535)	(0.00438)	(0.00450)	(0.00452)	(0.00455)
Constant	0.0115***	-0.165***	-0.161***	-0.0896***	-0.0719***	-0.0695***	-0.0577***	-0.0383***	-0.0104***	-0.0167***	-0.0306***	-0.0140***
	(0.00110)	(0.00647)	(0.00588)	(0.00360)	(0.00338)	(0.00416)	(0.00432)	(0.00338)	(0.00274)	(0.00282)	(0.00295)	(0.00276)
Observations	129,450	126,943	126,880	125,605	125,711	125,256	124,727	123,672	122,665	121,464	118,241	115,275
R-squared	0.023	0.186	0.163	0.095	0.076	0.084	0.085	0.067	0.046	0.048	0.048	0.046

New Zealand

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	March	April	May	June	July	August	September	October	November	December	January	February
Dummy (quartile = 2)	-0.00164	0.0194**	0.0181*	0.00495	0.00835	0.00617	0.0204*	0.0245**	0.0238**	0.0282**	0.0324***	0.0347***
	(0.00650)	(0.00921)	(0.00926)	(0.0104)	(0.0112)	(0.0120)	(0.0109)	(0.0111)	(0.0115)	(0.0118)	(0.0114)	(0.0124)
Dummy (quartile = 3)	0.0125**	0.0498***	0.0307***	0.0142	0.0213*	0.0241**	0.0388***	0.0341***	0.0329***	0.0393***	0.0538***	0.0586***
	(0.00601)	(0.00891)	(0.00872)	(0.00973)	(0.0109)	(0.0112)	(0.0113)	(0.0109)	(0.0124)	(0.0115)	(0.0115)	(0.0111)
Dummy (quartile = 4)	0.00293	0.0532***	0.0308***	0.0123	0.0199**	0.0225**	0.0455***	0.0449***	0.0462***	0.0650***	0.0793***	0.0811***
	(0.00646)	(0.00837)	(0.00790)	(0.00866)	(0.00999)	(0.0104)	(0.0101)	(0.0109)	(0.0116)	(0.0121)	(0.0117)	(0.0125)
Constant	0.00269	-0.0966***	-0.0578***	-0.0230***	-0.0230***	-0.0140*	-0.0279***	-0.0174**	0.00629	-0.0146*	-0.0302***	-0.0241***
	(0.00429)	(0.00606)	(0.00578)	(0.00648)	(0.00722)	(0.00763)	(0.00723)	(0.00697)	(0.00791)	(0.00782)	(0.00757)	(0.00798)
Observations	15,912	15,435	15,720	15,645	15,499	15,379	15,170	15,064	14,965	14,787	14,653	14,510
R-squared	0.065	0.118	0.109	0.099	0.100	0.106	0.108	0.101	0.095	0.097	0.102	0.096

United Kingdom

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	March	April	May	June	July	August	September	October	November	December	January	February
Dummy (quartile = 2)	0.00499	0.0282***	0.0269***	0.0252***	0.0193***	0.0164**	0.0165**	0.0266***	0.0336***	0.0321***	0.0444***	0.0461***
	(0.00390)	(0.00526)	(0.00512)	(0.00608)	(0.00657)	(0.00744)	(0.00740)	(0.00815)	(0.00817)	(0.00825)	(0.00849)	(0.00887)
Dummy (quartile = 3)	0.00718**	0.0328***	0.0341***	0.0314***	0.0291***	0.0292***	0.0355***	0.0472***	0.0553***	0.0567***	0.0701***	0.0787***
	(0.00282)	(0.00482)	(0.00476)	(0.00493)	(0.00535)	(0.00670)	(0.00637)	(0.00712)	(0.00759)	(0.00780)	(0.00836)	(0.00894)
Dummy (quartile = 4)	0.0128***	0.0478***	0.0477***	0.0519***	0.0482***	0.0479***	0.0592***	0.0743***	0.0829***	0.0837***	0.0973***	0.108***
	(0.00423)	(0.00622)	(0.00629)	(0.00626)	(0.00611)	(0.00643)	(0.00694)	(0.00769)	(0.00852)	(0.00876)	(0.00936)	(0.00998)
Constant	-0.00369	-0.0515***	-0.0529***	-0.0419***	-0.0238***	-0.0206***	-0.0262***	-0.0401***	-0.0515***	-0.0537***	-0.0661***	-0.0706***
	(0.00245)	(0.00357)	(0.00349)	(0.00383)	(0.00397)	(0.00453)	(0.00428)	(0.00485)	(0.00522)	(0.00528)	(0.00571)	(0.00607)
Observations	21,385	20,657	20,539	20,407	20,354	20,158	19,963	19,798	19,647	19,413	19,284	19,192
R-squared	0.041	0.087	0.080	0.075	0.062	0.062	0.068	0.083	0.096	0.101	0.112	0.115

B: Log change in firm-level employment since February 2019

Australia

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.00460**	0.0102***	0.0159***	0.0264***	0.0261***	0.0242***	0.0234***	0.0267***	0.0235***	0.0266***	0.0415***	0.0317***
	(0.00192)	(0.00225)	(0.00261)	(0.00283)	(0.00323)	(0.00300)	(0.00334)	(0.00327)	(0.00330)	(0.00338)	(0.00357)	(0.00369)
Dummy (quartile = 3)	0.00642***	0.0133***	0.0210***	0.0367***	0.0344***	0.0369***	0.0377***	0.0419***	0.0416***	0.0429***	0.0661***	0.0566***
	(0.00195)	(0.00257)	(0.00290)	(0.00306)	(0.00355)	(0.00379)	(0.00377)	(0.00418)	(0.00372)	(0.00372)	(0.00424)	(0.00410)
Dummy (quartile = 4)	0.0140***	0.0276***	0.0386***	0.0648***	0.0651***	0.0677***	0.0735***	0.0793***	0.0791***	0.0878***	0.116***	0.108***
	(0.00196)	(0.00268)	(0.00266)	(0.00331)	(0.00378)	(0.00395)	(0.00466)	(0.00506)	(0.00460)	(0.00492)	(0.00487)	(0.00524)
Constant	0.00622***	-0.00620***	-0.0199***	-0.00927***	-0.0193***	-0.0246***	-0.00829***	-0.00937***	-0.0118***	-0.0149***	-0.0397***	-0.0187***
	(0.00125)	(0.00159)	(0.00170)	(0.00183)	(0.00222)	(0.00232)	(0.00247)	(0.00265)	(0.00237)	(0.00243)	(0.00256)	(0.00262)
Observations	99,455	98,087	97,072	94,563	94,010	93,146	92,721	92,037	91,075	90,524	90,128	89,676
R-squared	0.014	0.021	0.020	0.032	0.032	0.030	0.030	0.031	0.028	0.035	0.043	0.038

New Zealand

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.0174***	0.0127	0.0137	0.0165	0.0287**	0.0255**	0.0305**	0.0362***	0.0330***	0.0340**	0.0349**	0.0397***
	(0.00636)	(0.00838)	(0.00926)	(0.0115)	(0.0123)	(0.0126)	(0.0119)	(0.0116)	(0.0119)	(0.0134)	(0.0139)	(0.0140)
Dummy (quartile = 3)	0.0129*	0.0210**	0.0290***	0.0395***	0.0399***	0.0405***	0.0487***	0.0551***	0.0599***	0.0649***	0.0634***	0.0643***
	(0.00669)	(0.00888)	(0.00945)	(0.0103)	(0.0106)	(0.0111)	(0.0108)	(0.0116)	(0.0114)	(0.0122)	(0.0124)	(0.0121)
Dummy (quartile = 4)	0.0287***	0.0487***	0.0567***	0.0734***	0.0818***	0.0927***	0.0952***	0.107***	0.107***	0.117***	0.118***	0.119***
	(0.00664)	(0.00883)	(0.00942)	(0.0108)	(0.0109)	(0.0109)	(0.0115)	(0.0119)	(0.0133)	(0.0132)	(0.0132)	(0.0140)
Constant	-0.0155***	-0.0284***	-0.0366***	-0.0464***	-0.0462***	-0.0487***	-0.0321***	-0.0379***	-0.0193**	-0.0252***	-0.0349***	-0.0191**
	(0.00408)	(0.00547)	(0.00581)	(0.00683)	(0.00703)	(0.00713)	(0.00701)	(0.00734)	(0.00783)	(0.00849)	(0.00853)	(0.00862)
Observations	11,032	10,869	10,809	10,655	10,525	10,394	10,291	10,189	10,095	10,006	9,877	9,852
R-squared	0.093	0.104	0.121	0.131	0.111	0.118	0.106	0.109	0.107	0.107	0.115	0.108

United Kingdom

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.00136	0.000610	0.000254	0.00971	0.0115	0.0102	0.00930	0.0197*	0.0273**	0.0307**	0.0374***	0.0323***
	(0.00566)	(0.00753)	(0.00774)	(0.00935)	(0.0116)	(0.0130)	(0.0125)	(0.0120)	(0.0133)	(0.0127)	(0.0142)	(0.0124)
Dummy (quartile = 3)	0.00372	0.00438	0.00867	0.0142*	0.0190**	0.0198**	0.0193*	0.0345***	0.0356***	0.0401***	0.0517***	0.0542***
	(0.00446)	(0.00521)	(0.00632)	(0.00750)	(0.00950)	(0.00945)	(0.0103)	(0.00953)	(0.0105)	(0.0109)	(0.0118)	(0.0109)
Dummy (quartile = 4)	0.0171***	0.0215***	0.0207**	0.0261**	0.0351***	0.0406***	0.0446***	0.0680***	0.0811***	0.0866***	0.102***	0.106***
	(0.00508)	(0.00732)	(0.00857)	(0.0103)	(0.0125)	(0.0123)	(0.0130)	(0.0111)	(0.0117)	(0.0117)	(0.0128)	(0.0121)
Constant	0.00567	0.0128***	0.0155***	0.0168***	0.0213***	0.0223***	0.0261***	0.00645	0.00186	-0.00828	-0.0187**	-0.0192**
	(0.00350)	(0.00441)	(0.00503)	(0.00618)	(0.00783)	(0.00802)	(0.00816)	(0.00734)	(0.00799)	(0.00804)	(0.00901)	(0.00793)
Observations	13,967	13,612	13,526	13,369	13,249	13,161	13,025	12,892	12,780	12,602	12,509	12,415
R-squared	0.061	0.061	0.073	0.075	0.071	0.064	0.060	0.073	0.073	0.069	0.072	0.072

Notes: The tables show econometric estimates of Equation 1, on a country-by-country basis (i.e. not pooled data). In all cases, the models control for the battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

Table B.4. Firm expansion or contraction: the role of productivity

A: Probability a firm expands workforce since February 2020

	March	April	May	June	July	August	September	October	November	December	January 21	February 21
Log productivity	-0.00141	0.0191***	0.0167***	0.0195***	0.0160***	0.0148***	0.0186***	0.0192***	0.0173***	0.0206***	0.0240***	0.0229***
	(0.00148)	(0.00159)	(0.00159)	(0.00184)	(0.00209)	(0.00211)	(0.00215)	(0.00210)	(0.00228)	(0.00222)	(0.00218)	(0.00230)
Constant	0.197***	-0.0825***	-0.0433**	-0.0190	0.0454*	0.0788***	0.0538**	0.0656***	0.114***	0.0730***	0.0389	0.0715***
	(0.0176)	(0.0189)	(0.0189)	(0.0218)	(0.0248)	(0.0250)	(0.0255)	(0.0249)	(0.0271)	(0.0264)	(0.0259)	(0.0273)
Observations	166,747	163,035	163,139	161,657	161,564	160,793	159,860	158,534	157,277	155,664	152,178	148,977
R-squared	0.055	0.034	0.033	0.031	0.032	0.038	0.038	0.038	0.039	0.036	0.036	0.037

B: Probability a firm contracts workforce since February 2020

	March	April	May	June	July	August	September	October	November	December	January 21	February 21
Log productivity	-0.0234***	-0.0583***	-0.0541***	-0.0460***	-0.0413***	-0.0401***	-0.0395***	-0.0376***	-0.0337***	-0.0360***	-0.0404***	-0.0401***
	(0.00172)	(0.00341)	(0.00295)	(0.00239)	(0.00216)	(0.00229)	(0.00224)	(0.00195)	(0.00168)	(0.00172)	(0.00177)	(0.00180)
Constant	0.429***	0.996***	0.961***	0.835***	0.772***	0.758***	0.751***	0.725***	0.666***	0.704***	0.766***	0.759***
	(0.0204)	(0.0405)	(0.0350)	(0.0283)	(0.0256)	(0.0272)	(0.0267)	(0.0231)	(0.0199)	(0.0204)	(0.0210)	(0.0213)
Observations	166,747	163,035	163,139	161,657	161,564	160,793	159,860	158,534	157,277	155,664	152,178	148,977
R-squared	0.153	0.282	0.273	0.228	0.198	0.190	0.184	0.168	0.145	0.148	0.144	0.137

Note: The tables show econometric estimates of Equation 1, using pooled cross-country data. In all cases, the models control for the battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

Table B.5. Firm-level hours worked responsiveness to lagged productivity quartile

A: Log change in hours worked since February 2020

Australia

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.0272***	0.0943***	0.0645***	0.0497***	0.0400***	0.0361***	0.0237***	0.00986	-0.00166	-0.00531	0.00483	0.00288
	(0.00356)	(0.0116)	(0.00882)	(0.00756)	(0.00593)	(0.00698)	(0.00798)	(0.00605)	(0.00526)	(0.00501)	(0.00610)	(0.00530)
Dummy (quartile = 3)	0.0484***	0.163***	0.111***	0.0823***	0.0652***	0.0638***	0.0565***	0.0332***	0.0152**	0.000467	0.0173***	0.0110**
	(0.00433)	(0.0165)	(0.0118)	(0.00881)	(0.00722)	(0.00940)	(0.00913)	(0.00749)	(0.00593)	(0.00534)	(0.00620)	(0.00550)
Dummy (quartile = 4)	0.0584***	0.203***	0.137***	0.0987***	0.0880***	0.0890***	0.0802***	0.0537***	0.0370***	0.0206***	0.0394***	0.0411***
	(0.00564)	(0.0184)	(0.0130)	(0.00995)	(0.00777)	(0.0115)	(0.0100)	(0.00822)	(0.00675)	(0.00578)	(0.00833)	(0.00611)
Constant	-0.0135***	-0.344***	-0.180***	-0.129***	-0.0629***	-0.0660***	-0.0624***	0.00471	0.0358***	-0.0116***	-0.0910***	-0.0211***
	(0.00314)	(0.0112)	(0.00803)	(0.00614)	(0.00478)	(0.00653)	(0.00630)	(0.00489)	(0.00378)	(0.00326)	(0.00425)	(0.00339)
Observations	121,652	115,155	115,065	114,945	115,281	114,895	114,452	114,115	113,653	112,540	110,003	107,680
R-squared	0.034	0.137	0.105	0.059	0.048	0.065	0.057	0.048	0.028	0.031	0.023	0.020

New Zealand

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.0190*	-0.0468*	-0.0100	-0.0112	-0.00216	0.0171	0.0348**	0.0217	0.0179	-0.00793	-0.0272*	0.0256
	(0.0105)	(0.0260)	(0.0184)	(0.0147)	(0.0153)	(0.0160)	(0.0160)	(0.0167)	(0.0168)	(0.0162)	(0.0165)	(0.0163)
Dummy (quartile = 3)	0.0339***	0.0116	0.0209	0.0150	0.0159	0.0344**	0.0307**	0.0203	0.0203	-0.0184	-0.0374**	0.0311**
	(0.0101)	(0.0251)	(0.0192)	(0.0160)	(0.0170)	(0.0166)	(0.0156)	(0.0164)	(0.0159)	(0.0145)	(0.0149)	(0.0155)
Dummy (quartile = 4)	0.0485***	0.0771***	0.0418**	0.0207	0.0306**	0.0424**	0.0519***	0.0353**	0.0271	-0.00976	-0.00265	0.0628***
	(0.00969)	(0.0237)	(0.0175)	(0.0154)	(0.0148)	(0.0165)	(0.0158)	(0.0177)	(0.0184)	(0.0149)	(0.0162)	(0.0173)
Constant	-0.0160**	-0.533***	-0.101***	-0.0644***	0.0163	0.0109	0.0189*	0.0453***	0.0668***	-0.0251**	-0.109***	-0.0589***
	(0.00681)	(0.0160)	(0.0121)	(0.00990)	(0.0105)	(0.0110)	(0.0106)	(0.0115)	(0.0116)	(0.01000)	(0.0102)	(0.0109)
Observations	15,674	14,441	15,121	15,209	15,108	15,041	14,875	14,787	14,686	14,518	14,364	14,241
R-squared	0.053	0.122	0.108	0.089	0.078	0.088	0.082	0.080	0.079	0.079	0.070	0.073

United Kingdom

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.0553***	0.124***	0.128***	0.148***	0.0575***	0.0345**	0.0237*	0.0350***	0.0603***	0.0393**	0.0707***	0.0562***
	(0.00860)	(0.0231)	(0.0236)	(0.0215)	(0.0136)	(0.0147)	(0.0124)	(0.0135)	(0.0176)	(0.0168)	(0.0186)	(0.0196)
Dummy (quartile = 3)	0.0569***	0.177***	0.156***	0.173***	0.0608***	0.0286*	0.0557***	0.0461***	0.0790***	0.0650***	0.0960***	0.0987***
	(0.00795)	(0.0241)	(0.0250)	(0.0232)	(0.0152)	(0.0160)	(0.0126)	(0.0139)	(0.0166)	(0.0164)	(0.0201)	(0.0202)
Dummy (quartile = 4)	0.0658***	0.249***	0.242***	0.268***	0.122***	0.0691***	0.0803***	0.0895***	0.122***	0.106***	0.145***	0.153***
	(0.00914)	(0.0268)	(0.0230)	(0.0241)	(0.0146)	(0.0147)	(0.0136)	(0.0138)	(0.0188)	(0.0180)	(0.0216)	(0.0208)
Constant	-0.0422***	-0.578***	-0.543***	-0.453***	-0.0846***	-0.0481***	-0.0278***	-0.0263***	-0.110***	-0.0688***	-0.148***	-0.174***
	(0.00536)	(0.0158)	(0.0156)	(0.0153)	(0.00872)	(0.00982)	(0.00762)	(0.00854)	(0.0114)	(0.0110)	(0.0135)	(0.0131)
Observations	19,830	16,856	16,779	17,433	18,102	18,359	18,232	18,039	17,871	17,512	17,474	17,327
R-squared	0.071	0.166	0.143	0.143	0.057	0.050	0.045	0.055	0.078	0.067	0.087	0.093

B: Log change in hours worked since February 2019

Australia

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.00452	0.0173***	0.0139***	0.0229***	0.0253***	0.0172***	0.0142***	0.0150***	0.00730	0.0112*	0.0235***	0.0209***
	(0.00294)	(0.00338)	(0.00381)	(0.00429)	(0.00457)	(0.00465)	(0.00514)	(0.00467)	(0.00578)	(0.00609)	(0.00643)	(0.00603)
Dummy (quartile = 3)	0.00734**	0.0222***	0.0214***	0.0392***	0.0385***	0.0291***	0.0318***	0.0339***	0.0297***	0.0289***	0.0508***	0.0464***
	(0.00320)	(0.00345)	(0.00404)	(0.00484)	(0.00512)	(0.00550)	(0.00561)	(0.00559)	(0.00519)	(0.00558)	(0.00701)	(0.00581)
Dummy (quartile = 4)	0.0139***	0.0417***	0.0436***	0.0571***	0.0675***	0.0612***	0.0687***	0.0735***	0.0674***	0.0709***	0.100***	0.0970***
	(0.00287)	(0.00404)	(0.00440)	(0.00475)	(0.00537)	(0.00568)	(0.00558)	(0.00625)	(0.00600)	(0.00660)	(0.00806)	(0.00671)
Constant	0.0800***	-0.00527**	0.0631***	-0.000706	0.0423***	0.0541***	0.0184***	0.0631***	0.0528***	-0.0375***	-0.0666***	-0.000256
	(0.00199)	(0.00225)	(0.00257)	(0.00303)	(0.00334)	(0.00347)	(0.00344)	(0.00354)	(0.00348)	(0.00378)	(0.00465)	(0.00386)
Observations	94,372	92,974	92,014	89,335	88,867	88,262	87,584	86,929	86,212	85,389	84,783	84,661
R-squared	0.006	0.011	0.011	0.012	0.015	0.015	0.014	0.015	0.016	0.023	0.025	0.018

New Zealand

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	0.0128	0.00818	0.0167	0.0217	0.0292*	0.0139	0.00890	0.0129	0.00331	-0.00521	-0.0247	0.0319*
	(0.00976)	(0.0123)	(0.0170)	(0.0167)	(0.0176)	(0.0179)	(0.0174)	(0.0193)	(0.0193)	(0.0223)	(0.0211)	(0.0190)
Dummy (quartile = 3)	0.0124	0.00932	0.0460***	0.0516***	0.0487***	0.0443**	0.0286	0.0540***	0.0508***	0.0434**	0.00305	0.0663***
	(0.00981)	(0.0126)	(0.0148)	(0.0175)	(0.0164)	(0.0177)	(0.0176)	(0.0159)	(0.0172)	(0.0194)	(0.0184)	(0.0177)
Dummy (quartile = 4)	0.0331***	0.0329**	0.0755***	0.0779***	0.0946***	0.0996***	0.0977***	0.111***	0.0951***	0.0738***	0.0510***	0.125***
	(0.0112)	(0.0149)	(0.0151)	(0.0191)	(0.0174)	(0.0178)	(0.0180)	(0.0180)	(0.0180)	(0.0213)	(0.0190)	(0.0183)
Constant	0.105***	-0.0573***	0.0598***	-0.00934	0.0417***	0.0564***	0.0382***	0.0488***	0.0818***	-0.0787***	-0.0896***	-0.00969
	(0.00674)	(0.00860)	(0.0101)	(0.0116)	(0.0110)	(0.0115)	(0.0110)	(0.0116)	(0.0118)	(0.0143)	(0.0128)	(0.0119)
Observations	10,910	10,743	10,690	10,525	10,404	10,268	10,168	10,059	9,975	9,883	9,742	9,734
R-squared	0.056	0.068	0.100	0.094	0.082	0.093	0.086	0.085	0.076	0.072	0.075	0.076

United Kingdom

	(1) March	(2) April	(3) May	(4) June	(5) July	(6) August	(7) September	(8) October	(9) November	(10) December	(11) January	(12) February
Dummy (quartile = 2)	-0.000259	0.0181*	0.00519	0.0122	0.0227*	0.0215	0.0225*	0.0346**	0.0388**	0.0454***	0.0445***	0.0358**
	(0.00996)	(0.0109)	(0.0119)	(0.0139)	(0.0134)	(0.0151)	(0.0134)	(0.0166)	(0.0158)	(0.0159)	(0.0170)	(0.0155)
Dummy (quartile = 3)	0.0106	0.0217*	0.0119	0.0163	0.0130	0.0257	0.0347**	0.0433***	0.0477***	0.0654***	0.0768***	0.0572***
	(0.00840)	(0.0125)	(0.0135)	(0.0142)	(0.0148)	(0.0156)	(0.0155)	(0.0167)	(0.0172)	(0.0156)	(0.0203)	(0.0182)
Dummy (quartile = 4)	0.0428***	0.0771***	0.0767***	0.0675***	0.0834***	0.104***	0.0998***	0.121***	0.134***	0.150***	0.170***	0.158***
	(0.0124)	(0.0155)	(0.0176)	(0.0186)	(0.0203)	(0.0208)	(0.0191)	(0.0197)	(0.0200)	(0.0196)	(0.0204)	(0.0212)
Constant	0.0713***	0.0680***	0.103***	0.0684***	0.137***	0.0957***	0.0883***	0.118***	0.0740***	0.0461***	0.0534***	0.0231**
	(0.00549)	(0.00769)	(0.00904)	(0.00986)	(0.0103)	(0.0109)	(0.0101)	(0.0116)	(0.0114)	(0.0107)	(0.0119)	(0.0118)
Observations	12,629	12,318	12,173	12,105	11,866	11,890	11,802	11,534	11,561	11,394	11,220	11,220
R-squared	0.043	0.059	0.053	0.058	0.056	0.050	0.052	0.062	0.062	0.063	0.057	0.065

Notes: The tables show econometric estimates of Equation 1, on a country-by-country basis (i.e. not pooled data). In all cases, the models control for the battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

Table B.6. Firm expansion or contraction: the role of productivity and technology

A: Probability a firm expands workforce since February 2020

	March	April	May	June	July	August	September	October	November	December	January 21	February 21
Log productivity	-0.00212	0.0185***	0.0161***	0.0189***	0.0154***	0.0138***	0.0175***	0.0180***	0.0161***	0.0194***	0.0228***	0.0216***
	(0.00147)	(0.00158)	(0.00159)	(0.00183)	(0.00208)	(0.00210)	(0.00214)	(0.00209)	(0.00228)	(0.00222)	(0.00218)	(0.00229)
Dummy apps >= 5	0.0251***	0.0247***	0.0220***	0.0217***	0.0228***	0.0340***	0.0382***	0.0436***	0.0424***	0.0426***	0.0415***	0.0433***
	(0.00387)	(0.00366)	(0.00352)	(0.00386)	(0.00426)	(0.00448)	(0.00447)	(0.00478)	(0.00510)	(0.00512)	(0.00503)	(0.00526)
Constant	0.203***	-0.0765***	-0.0379**	-0.0136	0.0510**	0.0872***	0.0631**	0.0763***	0.125***	0.0836***	0.0493*	0.0824***
	(0.0175)	(0.0187)	(0.0189)	(0.0217)	(0.0247)	(0.0249)	(0.0254)	(0.0248)	(0.0270)	(0.0263)	(0.0258)	(0.0271)
Observations	166,747	163,035	163,139	161,657	161,564	160,793	159,860	158,534	157,277	155,664	152,178	148,977
R-squared	0.055	0.034	0.034	0.031	0.033	0.038	0.039	0.039	0.040	0.036	0.036	0.037

B: Probability a firm contracts workforce since February 2020

	March	April	May	June	July	August	September	October	November	December	January 21	February 21
Log productivity	-0.0234***	-0.0583***	-0.0541***	-0.0462***	-0.0414***	-0.0402***	-0.0396***	-0.0376***	-0.0336***	-0.0359***	-0.0403***	-0.0400***
	(0.00171)	(0.00340)	(0.00293)	(0.00238)	(0.00214)	(0.00227)	(0.00222)	(0.00192)	(0.00166)	(0.00169)	(0.00175)	(0.00179)
Dummy apps >= 5	-0.000764	0.000826	0.00128	0.00848**	0.00638	0.00453	0.00126	-0.00118	-0.00237	-0.00345	-0.00462	-0.00258
	(0.00312)	(0.00390)	(0.00392)	(0.00385)	(0.00409)	(0.00405)	(0.00417)	(0.00424)	(0.00410)	(0.00430)	(0.00416)	(0.00437)
Constant	0.429***	0.997***	0.961***	0.837***	0.774***	0.759***	0.751***	0.725***	0.665***	0.703***	0.765***	0.758***
	(0.0203)	(0.0404)	(0.0349)	(0.0283)	(0.0255)	(0.0271)	(0.0264)	(0.0229)	(0.0198)	(0.0202)	(0.0208)	(0.0213)
Observations	166,747	163,035	163,139	161,657	161,564	160,793	159,860	158,534	157,277	155,664	152,178	148,977
R-squared	0.153	0.282	0.273	0.228	0.198	0.190	0.184	0.168	0.145	0.148	0.144	0.137

Note: The tables show econometric estimates of Equation 1, using pooled cross-country data. In all cases, the models control for the battery of fixed effects outlined in Section 4.1.
Source: Authors calculation based on Xero SBI.

Table B.7. Productivity-enhancing reallocation accelerates over the first half of 2020 – robustness

Estimated responsiveness of employment change since February (2020 or 2019) to productivity; balanced panel

Balanced sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Mar	Apr	May	June	July	August	September	October	November	December	January	February
Log productivity	0.00455***	0.0102***	0.0145***	0.0251***	0.0249***	0.0276***	0.0287***	0.0325***	0.0336***	0.0363***	0.0504***	0.0453***
	(0.000886)	(0.00130)	(0.00127)	(0.00162)	(0.00174)	(0.00170)	(0.00212)	(0.00220)	(0.00203)	(0.00215)	(0.00218)	(0.00241)
2020 dummy interacted with log productivity	0.00371**	0.0514***	0.0405***	0.0219***	0.0150***	0.0120***	0.0131***	0.00716**	0.00184	0.00228	-0.00515	-0.000738
	(0.00147)	(0.00438)	(0.00394)	(0.00316)	(0.00302)	(0.00329)	(0.00367)	(0.00335)	(0.00304)	(0.00314)	(0.00325)	(0.00339)
Constant	-0.0615***	-0.463***	-0.454***	-0.435***	-0.389***	-0.403***	-0.411***	-0.414***	-0.387***	-0.425***	-0.554***	-0.508***
	(0.00878)	(0.0263)	(0.0236)	(0.0189)	(0.0180)	(0.0197)	(0.0219)	(0.0200)	(0.0182)	(0.0188)	(0.0194)	(0.0202)
Observations	216,486	212,422	212,478	207,622	210,198	209,508	208,488	207,272	205,728	203,562	200,386	198,400
R-squared	0.031	0.159	0.139	0.088	0.072	0.073	0.073	0.065	0.053	0.056	0.061	0.059

Note: The tables show econometric estimates of Equation 1, using pooled cross-country data. In all cases, the models control for the battery of fixed effects outlined in Section 4.1. The sample is based on a balanced panel of firms, which we observe in both 2019 and 2020.
Source: Authors calculation based on Xero SBI.

Table B.8. Productivity and reallocation since the pandemic: role of firm size controls

Log change in firm-level employment since February 2020

February 2020 to:	A: February 2021		B: May 2020	
	(1)	(2)	(3)	(4)
Productivity	0.0410*** (0.00217)	0.0531*** (0.00258)	0.0609*** (0.00446)	0.0769*** (0.00496)
Productivity x New Zealand	-0.00456 (0.00608)	-0.000591 (0.00571)	-0.0444*** (0.00584)	-0.0466*** (0.00593)
Productivity x United Kingdom	0.0129** (0.00501)	0.0162*** (0.00660)	-0.0380*** (0.00522)	-0.0469*** (0.00556)
Fixed effects				
Ind, Reg, Cty	YES	YES	YES	YES
Size	YES	NO	YES	NO
Observations	148,977	148,977	163,139	163,139
R2	0.060	0.024	0.159	0.050

Note: The table augments the baseline model estimates in Table 1, by excluding firm size class fixed effects in columns 2 and 4.
Source: Authors calculation based on Xero SBI.

Table B.9. Productivity and reallocation since the pandemic: the role of technology – robustness

Log change in firm-level employment since February 2020

February 2020 to:	A: February 2021		B: May 2020	
	(1)	(2)	(3)	(4)
Productivity	0.0417*** (0.00181)	0.0419*** (0.00190)	0.0518*** (0.00323)	0.0520*** (0.00324)
High-tech dummy (>= 5 apps)	0.0207*** (0.00372)		0.0098*** (0.00300)	
Alternative tech dummy (>= 1 app)		0.00914*** (0.00296)		0.000837 (0.00188)
Fixed effects				
Ind, Reg, Cty, Size	YES	YES	YES	YES
Observations	148,977	148,977	163,139	163,139
R2	0.060	0.060	0.159	0.159

Note: The table augments the baseline model estimates in Table 1, by including High-tech dummies that equals one if a firm has at least 5 apps (or at least 1 app, under the alternate definition) connected in February 2020; zero otherwise.
Source: Authors calculation based on Xero SBI.