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The Effects of COVID-19 and JobKeeper on Productivity-Enhancing Reallocation in Australia

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Abstract

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Keywords

COVID-19, productivity, reallocation, recessions

JEL Classification

E24, E32, J63, O4

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The effects of COVID-19 and JobKeeper on productivity-enhancing reallocation in Australia

By Dan Andrews, Elif Bahar and Jonathan Hambur*

The consequences of the pandemic for potential output will partly hinge on its impact on productivity-enhancing reallocation. While recessions can accelerate this process, the more 'random' nature of the COVID-19 shock coupled with policy responses that prioritised preservation could disrupt productivity-enhancing reallocation. Our analysis based on novel high-frequency employment data for Australia shows that labour reallocation (and firm exit) remained connected to firm productivity over 2020 and 2021. However, outside of the initial acute phase of the shock the relationship weakened significantly compared to history. Australia's job retention scheme (JobKeeper) initially reinforced the connection between growth and productivity, supporting more productive firms. But it became more distortive over time and as the economy recovered.

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As economies recover from the COVID-19 pandemic, attention will invariably shift to the pandemic's impact on potential output. While the COVID-19 shock could impart lasting scars if it reduced educational attainment (via disruptions to schools) or the scope for knowledge spillovers (via less international worker mobility), there could be productivity benefits if the pandemic forced firms to make overdue investments in digitalisation and organisational practices. While these channels are likely relevant, they are not yet directly observable and act over long horizons. The emergence of real-time data sources provides an opportunity to get a timely gauge on the pandemic's impact on productivity-enhancing reallocation – the tendency for more productive firms to expand and less productive firms to contract (or exit). This is significant given evidence that COVID-19 represents a large shock to the nature and quantum of reallocation (Barrero, Bloom & Davis 2020), especially if new habits form from pandemic-induced experimentation with novel modes of business, work and consumption. However, the debate has so far has lacked a clear link with productivity.

The nature of economic downturns can fundamentally alter the extent of productivity-enhancing reallocation. The "cleansing" hypothesis posits that recessions can accelerate productivity-enhancing reallocation by lowering the opportunity costs of reallocation and provide a fertile breeding ground for firm restructuring, assuming that markets continue to select (scrap) the most (least) productive firms (Caballero & Hammour 1994; Schumpeter 1939). However, recessions can distort reallocation dynamics if an impaired financial sector leads reallocation to be driven by credit constraints, rather than underlying firm productivity. This could result in the premature shakeout of productive but financially fragile firms, and the destruction of valuable intangible capital (which is necessarily lost with business closure). The pandemic could provide a further twist on the cleansing hypothesis if workforce adjustments and business survival became detached from firm productivity owing to the broad-based nature of lockdowns, and crisis phase policies (i.e. job retention schemes) that prioritised preservation over reallocation to address other policy aims. Timely evidence on the impact of the pandemic on productivity-enhancing reallocation dynamics remains scarce.

Accordingly, this paper explores how the COVID-19 shock, as well as Australia's wage subsidy scheme ("JobKeeper"), shaped productivity-enhancing reallocation. We utilise novel high-frequency administrative tax data on employment outcomes from Single Touch Payroll (STP) collected by the Australian Tax Office (ATO) (Australian Tax Office 2021A), merged with firm-level measures of labour productivity, financial constraints and other relevant firm characteristics from ATO Business Income Tax (BIT) data for the 2018-19 financial year (Australian Tax Office 2020A, 2020B)). We then model dynamic allocative efficiency by estimating the responsiveness of firm-level employment changes (and exit) to pre-pandemic labour productivity, controlling for any differences in the shock across state-by-industry, and firm size and age classes. Andrews and Hansell (2021) show that the strong connection between (within-industry) labour reallocation and firm-level productivity significantly boosted Australian productivity growth over 2002-2016. We study how the pandemic influenced this connection.

Comparing the COVID period to the pre-COVID period using annual data, we find evidence that the relationship between reallocation and productivity strengthened during the early acute phase of the pandemic, before weakening sharply in the second half of 2020 and early 2021 as the pandemic wore on. Still, the relationship between firm growth and productivity remained positive, indicating that the COVID shock and policy did not completely sever the link. These patterns are also borne out using higher-frequency intra-year data, with the relationship strengthening sharply in April and May 2020, then stalling over the latter half of 2020.

These findings, are particularly interesting in the context of Australia's job preservation program, the JobKeeper Payment – the largest one-off fiscal measure in Australia's history – which supported more than 4 million individuals and over one million organisations and was in place from April 2020 to March 2021. The JobKeeper scheme aimed to support household incomes, reduce uncertainty and temporarily shield firm- and job-specific capital by maintaining the connection between workers and firms (Australian Government 2020). However, a key risk was that JobKeeper could result in 'zombification' if it delayed the restructuring of unproductive firms that would have downsized or exited in absence of the virus. If realised, this could have crowded out growth opportunities for more productive firms, reminiscent of the rise of zombie firms in Europe (Andrews, McGowan & Millot 2017).

To examine whether and how the JobKeeper program contributed to the changes in the relationship between productivity and growth, we test if the reallocation-productivity link varied with the share of workers receiving the JobKeeper subsidy. We do so at the local labour market level, after controlling for the size of the local economic shock, using administrative data from the JobKeeper program (Australian Tax Office 2021B).

On average over the first phase of the program (April-September 2020) we find that productivity-enhancing reallocation was stronger in those local labour markets that had a higher proportion of their workforce in receipt of JobKeeper, even after accounting for economic conditions. However, the policy appears to have become more distortive over time. To illustrate, we examine what occurred when the payment began being phased out from September 2020, when the first phase of the JobKeeper scheme (henceforth JobKeeper 1.0) ended and firms had to re-qualify for the scheme's second stage (henceforth JobKeeper 2.0). In those local labour markets where a large amount of the workforce exited the scheme, more labour flowed towards high productivity firms, indicating a stronger reallocation-productivity link. This suggests that, if the payment had not been phased out, this productive reallocation may not have occurred as there was virtually no evidence of productivity-enhancing labour reallocation in those markets where workforce transitions off the scheme were minimal. Put another way, the policy appears to have been leading to a degree of distortive labour hoarding as the economy recovered, and as the policy was wound down this released labour to be reallocated to more productive uses. Overall then, it appears the JobKeeper program contributed to the strengthening, then weakening of the productivity-reallocation link in Australia. This finding is somewhat consistent with the literature on short-term work schemes, that shows they are most effective when used as an automatic stabiliser (Baleer *et al* 2016; Gehrke & Hochmuth 2021; Brey and Hertweck 2020).

The shift in policy from supportive to potentially distortive over time is consistent with the (pre-shock) characteristics of the firms that took-up the subsidy across the two policy regimes. Under JobKeeper 1.0, more productive firms – and especially financially constrained ones – were more likely to take-up the subsidy, thus helping to prevent scarring effects that can arise from the premature exit of dynamic firms. But JobKeeper 2.0 was more likely to subsidise less productive firms. The former result is consistent with firm dynamics models, which predict that in the face of uncertainty and some fixed costs of operation, high productivity firms are likely to take on the cost and continue operating given the higher expected value of doing so. However, as the economy recovered, only the worse performing firms, as well as the sectors still affected by restrictions, still qualified for the program. Put differently, the early stages of the program were characterised by broad uptake, including by high productivity firms. As the economy recovered, these firms no longer required that support, generally leaving less productive firms on the program.

Focusing on the first phase of the program, the greater resilience of high productivity firms to the pandemic raised aggregate labour productivity by an estimated 5.2 per cent, relative to a counterfactual where the pandemic completely severed the reallocation-productivity link (abstracting from changes in firm-level productivity). We estimate that about one-half of this aggregate gain (2.6 per cent) can be accounted for by the introduction of JobKeeper 1.0, and more specifically its tendency to disproportionately shield more productive firms. Had policymakers not begun to phase-out the JobKeeper scheme from late September 2020, and the economy therefore not experienced an additional 'burst' of efficient reallocation, aggregate labour productivity would have been an estimated 1.5 per cent lower by November 2020. While this drag may have been temporary as some reallocation would have invariably occurred when the scheme ended, the winding-up of the JobKeeper scheme on 28 March 2021 appears justified – on productivity grounds at least – especially in light of the macroeconomic recovery.

Our results suggest that job retention schemes can be an effective crisis tool. Indeed, without the JobKeeper scheme, there could have been more of an indiscriminate shakeout of high productivity firms, risking long-term scarring to potential output. Our findings also emphasise the need for job retention schemes, or at least their effects, to be temporary and for their design to evolve as there is a fine line between hibernation and zombification. Of course, this risk should be weighed against the other benefits of such policies, such as decreasing uncertainty.

Our contribution is threefold. First, we supply novel real-time insights, based on high quality administrative tax data, on the impact of the pandemic on productivity-enhancing reallocation. This is significant given that the seminal paper on the impact of the Great Recession on productivity-enhancing reallocation first appeared – in working paper version – some six years after Lehman Brothers collapsed (Foster, Grim & Haltiwanger 2016). Second, we provide some of the first systematic real-time evidence on the financial characteristics of firms that participate in job retention schemes and consequences for aggregate productivity. Third, we contribute to the broader debate on job retention schemes, and specifically the trade-off between short-term protection and the allocative distortions that may materialise over the longer horizons.

The next section explores how recessions – and especially the pandemic – may impact the reallocation process, and gives some background to Australia's job retention scheme. Section 2 describes the data and presents some preliminary descriptive evidence on firm performance since the onset of the pandemic. Section 3 presents new evidence on the evolution of productivity-enhancing reallocation dynamics since the onset of the pandemic. Sections 4-6 then explore the potential impact of the JobKeeper scheme on the process and the implications for aggregate productivity. The final section draws some key policy implications and concludes.

I. COVID-19, reallocation and productivity

A. Why focus on reallocation?

There are various channels through which the pandemic could affect potential output, spanning labour quality (e.g. via schooling disruptions), capital deepening (e.g. accelerated technology investment) and total factor productivity (TFP, e.g. business experimentation and reallocation) (di Mauro & Syverson 2020). Since many of these channels relate to forces that are not yet directly observable or that act over long horizons – e.g. the human capital impacts will not be known for decades – we aim to shed real-time evidence on the within-industry reallocation channel.

While COVID-19 has been characterised as a reallocation shock (Barrero, Bloom & David 2020), the debate has lacked a link with productivity, which, as discussed below, is crucial.

We focus on the labour reallocation channel by exploring how firm-level employment and exit changes since the onset of the pandemic are correlated with a firm's pre-shock level of labour productivity. Given its strong theoretical and empirical basis, this approach is likely to broadly be indicative of the pandemic's structural impulse on productivity via the reallocation channel. Furthermore, given that it does not require data on firm-level productivity during the crisis – which is notoriously volatile – it carries clear advantages from a measurement perspective.

Market economies are characterised by a resource reallocation process that has two key dimensions. Firstly, the rate of reallocation is high, with headline economic statistics concealing an intense churn 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 per cent and 10 per cent over 2004-2007, with these figures reversing as the crisis took hold (Criscuolo, Gal & Menon 2014). Firm entry (exit) typically accounts for one-quarter (one-third) of gross job creation (destruction).

Secondly, this reallocation process is strongly linked to firm-level productivity, particularly within narrowly defined industries, given the wide distribution of firm outcomes (Syverson 2004) and greater substitutability of inputs within sectors (Foster, Haltiwanger & Krizan 2001; Mora-Sanguinetti & Fuentes 2012). In particular, numerous papers have shown that: i) high productivity firms are more likely to expand and low productivity firms more likely contract and exit (Decker et al. 2020);[1] and ii) this process of (within-industry) resource reallocation materially boosts aggregate productivity growth (Bailey, Hulten & Campbell 1992; Disney et al. 2013).

It is crucial that the reallocation process is productivity-enhancing as it entails economic and human costs. Job destruction and firm exit can lead to losses of job-specific and organisational capital – both internal (i.e. tacit knowledge) and external (i.e. supply chain connections) to the firm. It can also lead to disruptions of job ladders and longer-term labour market scarring for workers (Jacobson et al. 1993; Davids & von Watcher 2011; Andrews et al. 2020). These costs are compounded when the process of downsizing and exit is not driven by productivity, as there is no scope for productivity-enhancing reallocation towards of the labour to more efficient producers (Pethokoukis 2020).

In many OECD countries, the productivity slowdown has been underpinned by a decline in the overall rate of job reallocation, as well as a weaker reallocation-productivity link (Decker et al. 2020). 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 & 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.

B. COVID-19: Cleansing or Scarring?

The impact of recessions on productivity-enhancing reallocation remains an open question, with debate centring on the extent to which recessions unleash cleansing or scarring dynamics. Recessionary episodes in United States from the 1940s to the early 2000s generally displayed cleansing dynamics (Davis, Faberman & Haltiwanger 2006, 2012; Davis & Haltiwanger 1990, 1992 & 1999; Davis, Haltiwanger & Schuh 1996; Foster, Haltiwanger & Krizan 2001). Reallocation accelerated – as the rise in job destruction more than offset

[1] These empirical studies take their structure from: i) the canonical models of firm dynamics whereby idiosyncratic shocks to productivity, demand, and costs impact the growth and survival of heterogeneous firms (Ericson & Pakes 1995; Hopenhayn 1992; Hopenhayn & Rogerson 1993; Jovanovic 1982); 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 & Willis 2007).

the decline in job creation – and was strongly linked to productivity, with job destruction and exit concentrated in lower productivity business units.

However, recessions may not always be associated with increased productivity-enhancing reallocation and may lead 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 & Pappadà 2015), it is notable that reallocation fell during the Global Financial Crisis – 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 & Haltiwanger 2014, 2016). Financial crises might impart scars if they reduce entrepreneurial finance (Buera & 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, successful start-ups have emerged during downturns testament to the ability of young firms to nimbly respond to changing market conditions (Calvino, Criscuolo & Verlhac 2020).

Compared to previous crises, the impact of the pandemic on this reallocation process is even more theoretically ambiguous for a range of reasons. On the one hand, the COVID-19 shock may have severely disrupted the typical reallocation process. In this view, the pandemic was a health shock that was exogenous to pre-crisis firm performance, and the collapse in mobility that followed – a function of both fear and broad-based lockdowns – affected all firms regardless of their productivity. This was reinforced by a crisis economic policy response that prioritised preservation (or hibernation) via job retention schemes and various measures to shield firm finances and prevent foreclosure. These forces had two consequences. First, the labour reallocation rate fell significantly, as job destruction was effectively curbed while there was limited scope for job creation. Second, the reallocation-productivity link may have been diminished, if not completely severed.

An alternative view posits that the reallocation-productivity link should remain intact – even if the overall rate of reallocation falls – 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, Bloom & David 2020). High productivity firms – due to their superior managerial practices (Bloom & Van Reenen 2007) – could more effectively accommodate teleworking and quickly 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.

Evidence on the impact of the pandemic on productivity-enhancing reallocation is scarce, partly due to the fact that few real-time datasets contain information on firm-level productivity. That said, the limited evidence is broadly consistent with the idea that reallocation declined but remained connected to productivity. Bloom et al. (2020) exploit survey data from the Decision Maker Panel and find that hours worked fell more sharply in 2020-Q2 for firms that had lower productivity (over 2017-2019). While this partly reflects the fact that the pandemic hit lower productivity sectors harder, the connection between the contraction of hours worked and firm productivity is also observed within sectors.[2]

Evidence from France and Japan shows that the number of firms filing for bankruptcy fell during 2020 but the factors that predicted firm failures in 2019 – primarily low productivity

[2]Bartik et al. (2020) speculates that the pandemic may have engendered 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".

and debt – were at work in a similar way in 2020 (Cros, Epaulard & Martin 2021; Hong, Kikuchi & Saito 2020). Further, evidence from several European countries (Croatia, Finland, Slovakia and Slovenia in Bighelli et al. 2021, and France in Cœuré 2021) found that low productivity or zombie firms did not disproportionately take-up support schemes, though the opposite is found in Freeman et al. (2021) for the Netherlands. 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 teleworking (Lamorgese et al. 2021).

C. Australia during COVID-19 and JobKeeper

Australia represents an interesting case study for analysis for a number of reasons. Following an initial sharp downturn in economic activity, Australia experienced a sharp recovery and was one of the first countries to return to pre-COVID levels of output and employment (Australian Government 2021b). Alongside excellent high-frequency data (discussed below), this allows us to examine the impacts of COVID-19 and related support packages on reallocation both during the downturn and the recovery.

That said, while most of the economy recovered quickly, certain sectors remained heavily constrained by restrictions including international border closures, while certain states, particularly Victoria, experienced additional lockdowns following second and third waves. This variations provides us with additional scope to identify the effects of COVID-19 and broad-based support policies.

Finally, as in other countries, Australia introduced a job retention scheme during the pandemic – JobKeeper – the effects of which can be analysed. JobKeeper was initially announced and introduced by the Australian Government on 30 March 2020. The policy supported over 4 million individuals and 1 million businesses (Australian Government 2021a), or around one-third of both, and had three objectives. First, it aimed to maintain links between firms and workers to facilitate a quick economic recovery and limit economic scarring.[3] Second, it was designed to provide income support, complementing increased generosity in welfare payments and other business support measures. Thirdly, the policy aimed to decrease uncertainty by ensuring a wage 'floor' (Australian Government 2020).

The scheme provided a flat rate of AUD$1,500 per fortnight to be paid to any eligible employees, and one eligible business participant (e.g. owner-manager) in a business. The subsidy was paid to eligible firms who passed it on in full to eligible workers. Eligible employees included all permanent staff, and any long-term casual staff (employed regularly for over one year). Eligibility on the firm side for the first stage of the scheme was dependent on having w reasonable expectation that the firm would experience a year-on-year decline in revenue, generally of more than 30 per cent, for at least one month. By qualifying once, firms qualified for the full six-month period of the first phase of the policy (April to September 2020). At the time the JobKeeper Payment was announced, it was expected that Australia would face significant restrictions for an extended period, meaning a high share of businesses were eligible.

In July 2020, the Australian Government announced that it would extend the scheme for another six months in two three-month extensions (October to December 2020, and January to March 2021). But the second and third phase had a materially different design. Eligibility for each extension would require the business to re-qualify by demonstrating an actual year-on-year decline in quarterly revenue, generally of at least 30 per cent, in the previous quarter. The payment rates were lowered, and a tiering system was introduced

[3] Analysing data for the first few months of the program, Bishop & Day (2020) estimate that JobKeeper reduced total employment losses by at least 700,000.

based on the employees' 'normal' hours.

Several aspects of the policy make it particularly interesting to examine. First, the three phases of the program, and its end in March 2021, allow us to track changes in labour reallocation as workers and firms flow on and off the program. This provides an excellent lens to examine its supportive or distortive impact on productivity-enhancing reallocation over time as the economy recovered.

The flat rate payment and prospective turnover requirements in the first stage also created potentially quite unique incentive structures. It created a strong incentive for the firm to ramp up production, given they only received direct benefits from the payments if their employees were working, as this turned the payment from an income transfer to employees, to a wage subsidy for firms (Australian Government 2021a). This incentive to increase activity and innovate could potentially lessen distortive aspects of the retention policy.

II. High-frequency firm-level data

If history is any guide, evidence on the impact of the pandemic on reallocation and productivity for some countries is still many years away. Lengthy time lags that characterise the release of suitable microdata sources, with establishment and 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). However we have a unique opportunity to shed light on this question by exploiting real-time administrative data from Single Touch Payroll (STP), collected by the Australian Tax Office (ATO) (Australian Tax Office 2021a).

A. Single Touch Payroll

The ATO receives payroll data from STP-enabled firms when the firm runs each payroll cycle.[4] This yields high-frequency data on jobs and wages which we merge with annual BIT data (from 2018-19) containing (value-added and turnover-based) measures of labour productivity, measures of financial health (i.e. liquidity) and firm characteristics (i.e. firm size, age and industry). Crucially, the dataset also contains flags for whether a firm was a recipient of JobKeeper.

STP has broad-based coverage across industries (Table B1), and we consider all States as well as the Australian Capital Territory and the Northern Territory. Employers with 20 or more employees (large employers) commenced transition to STP reporting on 1 July 2018, with approximately 99 per cent of large employers reporting through STP as at December 2020.[5] Employers with less than 20 employees (small employers) began transitioning to STP on 1 July 2019. This delayed transition coupled with a range of reporting concessions that the ATO made available to some small firms meant that approximately 77 per cent of small employers were reporting through STP as at the beginning of September 2020.[6] Payroll jobs reported via STP exclude owner managers of unincorporated enterprises.[7][8] Reporting is done on a jobs basis, instead of a heads basis like standard labour force statistics. Unfortunately, the dataset does not include hours, precluding analysis on this margin. However, Andrews, Charlton and Moore (2021) consider this using a smaller data

[4] A payroll job is a relationship between an employee and their employing enterprise, where the employee is paid in the reference period through STP-enabled payroll or accounting software and reported to the ATO.

[5] Payroll reporting via STP is still relatively new and some employers have been granted concessions to enable a longer transition period to mandatory STP reporting.

[6] Reporting concessions were made available to small firms if they: i) employ family members or other 'closely held' payees; ii) are micro employers with one to four employees; iii), employ intermittent or seasonal workers; or iv) do not have access to a reliable internet connection.

[7] Table B.2 in Appendix A contains summary statistics for our sample.

[8] Non-employing firms accounted for a large share of firms on JobKeeper, though a lower share of payments. Whether or not the results, or even conceptual frameworks, extend to these firms is unclear.

set based on Xero accounting software.

As discussed below, our econometric framework – through the inclusion of industry, state, firm size and firm age fixed effects – allows us to control for any minor differences in coverage, by focusing on firm dynamics within cells (i.e. industry, firm size and age classes, in a given state). We implement a range of data cleaning techniques that are customary in the literature including: i) winsorising key economic variables – such as labour productivity – at the top 1% and bottom 1% of the within-industry distribution; ii) excluding the government and not-for-profit sectors, as well as non-employing firms; iii) employment and labour productivity data for all subsidiaries firms in a consolidated entity is summed, and for some variables (e.g. industry, age), information is taken from the largest (by income) firm in the consolidation.

One downside of the STP data is that it has a limited pre-COVID history. As such, to take a longer-term view we also exploit annual firm-level Pay As You Go (PAYG) employment data from the Australian Bureau of Statistics Business Longitudinal Analysis Data Environment (ABS 2023). These data are very similar to the STP data used, but are available on a financial year basis indicating the number of workers employed by the firm in total over the year.

B. *Firm performance over the pandemic*

Figure 1 plots the evolution of STP jobs since the week ending 14 March 2020. Panel A shows total STP jobs fell sharply from March and troughed in mid-April, roughly a fortnight after JobKeeper was announced (on 30 March). Employment then recovers – retracing almost one-half of the initial decline within two months – before a COVID-19 outbreak in the state of Victoria in late June weighs on the national recovery. By November 2020, however, national employment has returned to around pre-shock levels and, looking through the seasonal volatility at the turn of the year, subsequently hovers around that level.

Aggregate movements however conceal significant heterogeneity. As is the case in other OECD countries, the decline in employment is concentrated in those hard-hit sectors centred on in-person services, with STP jobs in Accommodation and Food Services, for example, declining by around 35 per cent between early March and mid-April (Figure A1). The shock also hit smaller firms harder, with the decline in STP jobs in SMEs more than twice as large as that for larger firms through March-April 2020 (Figure 1, Panel B). Given that larger firms are more productive than SMEs in Australia (Andrews & Hansell 2021), this provides preliminary suggestive evidence of cleansing effects, but it could also reflect the sectoral composition of the shock if smaller firms are more prevalent in hard-hit sectors.

As is now well established, the labour market shock was buffered by the use of job retention schemes, which preserved the connection between workers and firms even if the number of hours they worked declined sharply.[9] Retention schemes were an effective crisis tool as they aimed to curtail job destruction. This can be seen from the sharp decline in job separations following the announcement of the JobKeeper scheme in late March (Figure 2), especially amongst subsidised firms who were generally hit harder by the shock and experienced a spike in separations (Panel B).

While the pandemic was associated with a fall in the overall rate of job reallocation, it

[9] Similar to other countries, Labour Force Survey (LFS) data shows that average hours worked falls much further than (a heads measure of) employment in Australia (Australian Bureau of Statistics 2021b). However, the LFS contains no data on the firm so it is not possible to explore how hours worked changes across the distribution of firm productivity.

(a) Total vs Victoria (b) By firm size

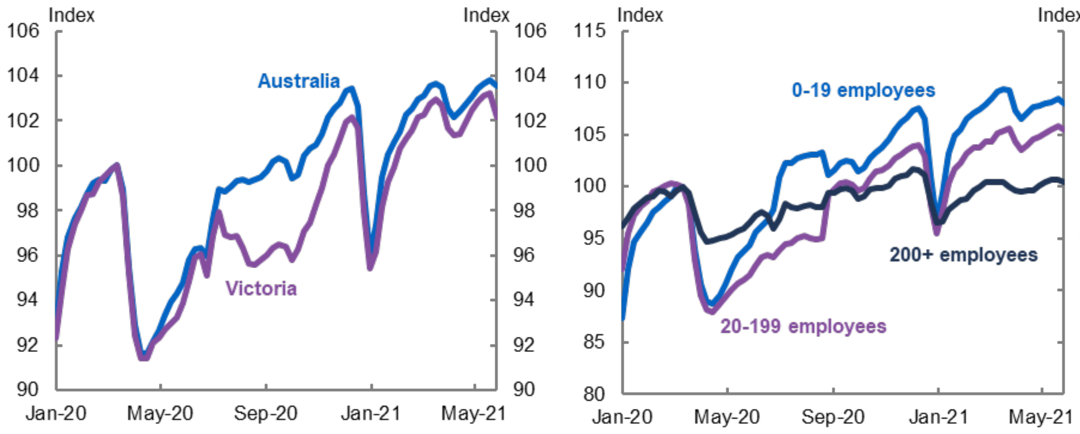

Figure 1. : Employment in Australia since March 2020

Notes: Payroll jobs by (a) region, and (b) firm size, indexed to week ending 14 March 2020.
Source: Australian Bureau of Statistics (2021a)

did not completely freeze creative destruction. Even after JobKeeper was announced, a non-trivial share of firms were still shedding workers and many firms were still growing over 2020 (Figure A2, Panel A). This diversity is significant in light of the widespread heterogeneity in firm productivity within narrowly-defined industries (Figure A2, Panel B; Syverson 2011), which creates scope for growth-enhancing resource reallocation towards more productive firms.[10] The rest of the paper explores how firm-level workforce adjustments were connected to a firm's rank in the (within-industry) labour productivity distribution.

(a) All firms (b) Subsidised (c) Not subsidised

Figure 2. : Job reallocation since onset of COVID-19

Notes: Hires and separations, indexed fortnight ending 1 March 2020. Hires and separations based on start and cease dates for a worker's employment relationship with a business. These include relationships with zero pay, which is one reason why the separations index can remain above the hiring index, despite paid payroll job levels having stabilised - an employment relationship can formally end sometime after paid work has ceased. Dotted line indicates announcement of JobKeeper.
Source: Authors' calculations based on de-identified STP tax data Australian Tax Office (2021a).

[10]Within our sample a firm at the 75th percentile of the within-industry labour productivity distribution produces around two times as much revenue per worker as a firm at the 25th percentile of the distribution.

III. COVID-19 and productivity-enhancing reallocation dynamics

A. Baseline model

The particular econometric framework we employ is that proposed by Decker et al (2020) based on a fairly general model of firm growth. Under this framework, all else equal (e.g. size, industry) more productive firms should grow their employment more quickly than less productive firms. But other factors such as frictions could influence the size of this gap, and so the strength of the relationship between productivity and employment growth.

This model yields the following, fairly simple regression framework:

$$E_{isr} = \alpha_0 + \beta_1 LP_{isr} + \chi_{isr} + \rho_{sr} + \epsilon_{isr} \tag{1}$$

where E is cumulative change in employment between March 2020 and subsequent points for the STP data, and over the financial year for the PAYG data, for firm i, in (4-digit) industry s, and state r. LP is the log level of firm-level labour productivity in 2018-19 for the STP data, or in the previous year for the annual regressions, computed as either value added or turnover per worker. We can also estimate a more flexible specification with dummy variables corresponding to the firm's quartile in the (within-industry) labour productivity distribution, with the lowest productivity quartile the base case. χ includes controls for firm size classes based on 2018-19 employment (<5, 5-19, 20-49, 50-199, 200+ employees), and firm age classes (<2, 3-5, 6-10, 11-19, 20+ years). Finally, ρ contains a battery of fixed effects at the industry and state level. Conceptually, industry fixed effects sweep-out differences in average industry performance at the national level (i.e. hospitality was hit harder by the pandemic than food retailing) while state fixed effects control for average differences in state performance (i.e. Victoria was hit harder than Western Australia). In practice, we include interacted state-industry fixed effects, which allows us to control for the fact that the pandemic hit firms harder in the hospitality sector in Victoria than in New South Wales. Standard errors are clustered at the state by industry level.

If β_1 >0 for our employment model, then looking within state-industry cells and holding firm size and age constant, more productive firms are more likely to expand and less productive firms are more likely to shed labour, suggesting that reallocation is productivity-enhancing. Likewise, when we replace employment growth with an indicator of firm exit in our exit model, β_1 <0 indicates that more productive firms are less likely to exit the market, again suggesting the productivity-reallocation link remained intact.

For the STP-based regressions we explore various sources of heterogeneity in the reallocation-productivity link. First, we test if the strength of the link varies across states by interacting LP with a Victoria dummy. Second, we explore differences across industries by interacting LP with a dummy variable for those industries centred on in-person services that were hit particularly hard by the pandemic. Third, we test if the reallocation-productivity link is stronger for smaller versus larger firms, and younger versus older firms, by interacting LP with firm size and age dummies. We also remove firms that enter the sample post-March 2020 given a lack of historical productivity data.

In our regressions, or measure of employment growth is defined as the change in firm-level employment divided by the average employment across both periods following Davis, Haltiwanger and Schuh (1996).

$$E_{i,t} = \frac{N_{i,t} - N_{i,t-1}}{\frac{N_{i,t} + N_{i,t-1}}{2}} * 100 \tag{2}$$

This measure is bounded between -200 and 200 and it is a second order approximation of the log difference for growth rates around zero. Further, it can accommodate exiting firms, in which case the function takes a value of -200 (exit).

The regression framework we have adopted is not the only approach to considering dynamic allocative efficiency. For example, Hsieh and Klenow (2009) use the dispersion in measured revenue-based MFP, assuming that any dispersion indicates a misallocation of resources. However, recent research argues that this only holds under a fairly restrictive set of assumptions that equalise marginal quantity-based MFP and average revenue-based MFP. If the assumptions do not hold, the measured dispersion reflects noise, as well as any true misallocation (Haltiwanger, Kulick and Syverson 2018). Other approaches, such as Baqaee and Fahri (2020), take a more structural approach. However, we follow the approach of Decker et al (2020) given its parsimony, transparency and robustness, and for easy comparison with Andrews and Hansell (2021).

B. Results with historical annual PAYG data

Table 1 shows the results for the annual PAYG data regressions. Column 1 estimates β_1 over the full 20 year sample, while the other columns allow it to change over time. As shown in Andrews and Hansell (2021), the relationship between growth and productivity has weakened over time, with our findings showing as similar decline to their earlier work up until the COVID period.[11] However, we see a strengthening in the relationship in the financial year 2019/20, whose last quarter contains the initial COVID shock. The relationship then weakens significantly in 2020/21, though remains positive. Both of these changes are statistically significant at the 1 per cent level, and are even more evident if we flexibly allow the relationship to differ over each year of the sample, with the coefficient increasing back up to levels last seen in 2013 before declining sharply (Figure 3). They are also robust to accounting for the 'standard' cyclically in the strength of the relationship, by including productivity interacted with the state-level unemployment rate (Column 3). [12]

C. Results with high-frequency STP data

The historical PAYG results suggest that the link between firm growth and productivity strengthened at the onset of COVID, then weakened, relative to pre-COVID. To understand these changes in more depth, we turn to high-frequency STP data. The first thing to note is that, consistent with the PAYG results, productivity and growth remained linked over the period. Table 3 (Panel A) shows estimates from regressions of the cumulative change in firm-level employment between March and May 2021 (Column 1) and firm exit probability (Column 3) on firm-level labour productivity in 2018-19. The coefficient on productivity is positive and statistically significant at the 1 per cent level in the employment growth model, and negative and significant in the exit model. We see the same thing using the more flexible specification in Columns 2 and 4, which show that firm-

[11] The coefficient in the base period of slightly over 5 is similar to that in Andrews and Hansell (2021), though they express it as 0.05. In both papers the coefficient declines by around one third.

[12] Note that the regression uses a single lag of productivity up to 2020/21, but uses the second lag for this year to avoid the effect of COVID on measured productivity. Using the second lag for all years leads to very similar patterns, though the magnitudes of the coefficients change somewhat, making the coefficients harder to compare to earlier papers.

Table 1—: Firm-level growth responsiveness to productivity – Historical data

	(1) Growth	(2) Growth	(3) Growth
Labour productivity	3.57	5.22	5.00
	(0.09)	(0.14)	(0.14)
Labour productivity 2008-2011 FY		-1.35	-1.30
		(0.10)	(0.10)
Labour productivity 2012-2019 FY		-1.75	-1.50
		(0.11)	(0.11)
Labour productivity 2020 FY		-1.53	-1.30
		(0.13)	(0.13)
Labour productivity 2021 FY		-4.31	-3.87
		(0.15)	(0.16)
Age FE	Yes	Yes	Yes
Size FE	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Productivity x State Unemployment	No	No	Yes
N	3,793,411	3,793,411	3,791,971
R-squared	0.055	0.056	0.056
Adjusted R-squared	0.054	0.054	0.054

Notes: Standard errors clustered at the state*industry level. R-squared are overall R-squared. Constant not shown.
Source: Authors' calculations based on administrative PAYG and BIT data (ABS 2023).

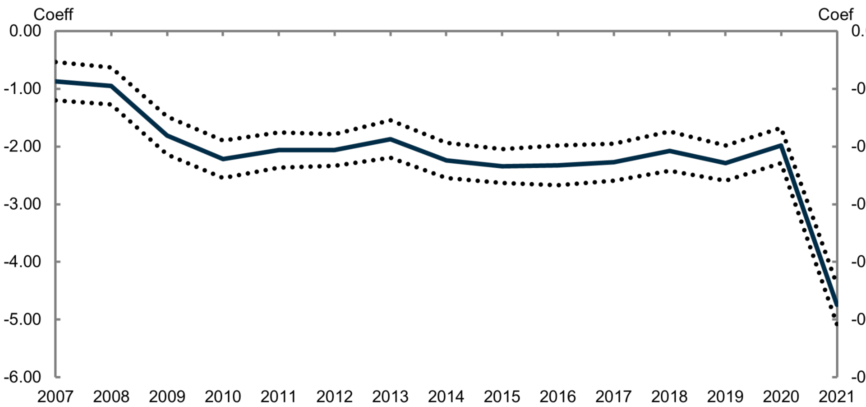

Figure 3. : Change in Productivity Coefficient Over Time

Notes: Coefficients from regression similar to that in Table 1 Column 2, but allowing the coefficient on productivity to change each year. Dotted lines show +/- 2 standard error bands.
Source: Authors' calculations based on administrative PAYG and BIT data (ABS 2023).

level employment performance and survival was strongest (weakest) in the highest (lowest) productivity quartile, and increasing in a monotonic fashion across the distribution. [13]

[13]Given net employment increased over this period, and many firms grew, the result was driven by labour moving between firms, rather than simply into unemployment.

These differences in firm performance are economically significant and carry important aggregate implications. Between March 2020 to May 2021, the implied difference in employment growth between a high productivity firm – i.e. one with LP one standard deviation (1.25 log points) above the industry mean – and a low productivity firm – i.e. one with LP one standard deviation below the industry mean – was 11.1 percentage points (Figure 4 Panel A). Similarly, the implied exit probability for a low productivity firm was around 5 percentage points higher than for a high productivity firm (Figure 4 Panel B), again indicating less productive firms were less resilient.[14]

Table 2—: Baseline results: Firm-level growth and exit responsiveness to productivity

	(1) Growth	(2) Growth	(3) Exit	(4) Exit
Labour productivity	4.415		-0.020	
	(0.144)		(0.001)	
Labour productivity Q2		5.965		-0.030
		(0.398)		(0.002)
Labour productivity Q3		9.932		-0.047
		(0.392)		(0.002)
Labour productivity Q4		12.627		-0.055
		(0.465)		(0.002)
Age FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Industry x State FE	Yes	Yes	Yes	Yes
N	404080	404080	404080	404080
R-squared	0.049	0.049	0.070	0.070
Adjusted R-squared	0.042	0.041	0.063	0.062

Notes: Regressions are all variations of Equation (2). Dependant variable in (1)-(2) is employment growth rate from March 2020 to May 2021. Dependant variable in (3)-(4) is dummy which equals one if firm has exited in May 2021. Standard errors clustered at the state*industry level. R-squared are overall R-squared. Labour productivity Q1 is the bottom quartile and is the base case. Constant not shown.
Source: Authors' calculations based on administrative STP and BIT data (Australian Tax Office 2020A, 2020B, 2021A).

As outlined in Section 6, this greater resilience of high productivity firms to the shock raised aggregate labour productivity by an estimated 5.2 per cent, relative to a counterfactual where the pandemic completely severed the link between reallocation and productivity (i.e. $\beta_1 = 0$ in equation 2). The corollary is that if this counterfactual was realised – and high and low productivity firms (within industry) adjusted identically to the shock – then the pandemic would have wiped-out 3 to 4 years' worth of aggregate labour productivity growth via distorted market selection and reallocation.[15] That said, compared to the case where the relationship had not weakened at all, productivity was still lower.

The results also suggest that firm employment adjustments and exit are most responsive to productivity amongst smaller firms (Figure 4; also Table B3). The same is true with respect to exit and productivity. The connection between reallocation and productivity

[14]Standard deviations of productivity by firm size are 1.24 log points for 0-4 employees, 1.15 for 5-19 employees, 2.21 for 20-49 employees, 1.40 for 50-199 employees, and 1.86 for 200 or more employees).
[15]In the 30 years prior to the pandemic, aggregate labour productivity growth averaged around 1.5 per cent per annum in Australia. Growth has been lower in recent years, suggesting an even bigger impact.

is also somewhat stronger amongst younger firms, but these differences are often not statistically significant (see Table B4).

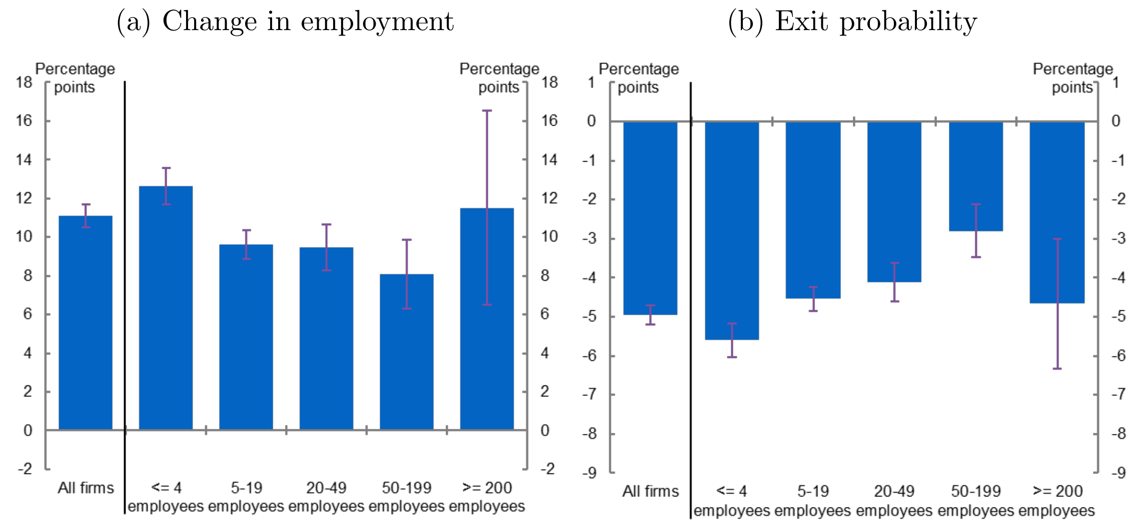

Figure 4. : Difference in performance between high and low productivity firms, by firm size

Notes: Plots predicted gap in growth between high and low productivity firms, where high and low productivity firms are +/- one standard deviations above the mean, respectively, of each firm size sub-group. Standard deviation of productivity range from 1.1-1.5 log points. Coefficients taken from baseline regression run on firm size sub-samples, as indicated in chart. Ranges show estimates using upper and lower bounds of 90 per cent confidence intervals on the coefficients. Econometric estimates underlying chart are in Table B3.
Source: Authors' calculations based on administrative STP and BIT data (Australian Tax Office 2020A, 2020B, 2021A).

Between March and May 2020, the reallocation-productivity link is strongest for the Australian economy as a whole (Figure 5). This is the period where lock-downs were initially introduced across states and territories, before they began to be eased in June. Thereafter it weakens, but the resurgence of COVID-19 in Victoria from June underpins a pick-up in this relationship in Victoria. A similar pattern is evident for the the Omicron wave of COVID, which led to lockdowns in Victoria and New South Wales around September 2021.

In the early months of the pandemic, we also observe a stronger reallocation-productivity link in hard-hit industries, suggesting that job losses were disproportionately concentrated in lower productivity firms in activities such as Hospitality, and Arts and Recreation (see Figure A3). A similar pattern is not observed over the same period in 2021, suggesting it does not only reflect seasonal patterns. Taken together results suggest that productivity-enhancing reallocation was strongest when economic activity was weakest, consistent with the cleansing hypothesis described in Section 1. However, we cannot rule out the possibility that some of these patterns do reflect some normal seasonal patterns, given the lack of historical STP data.

Interestingly, the relationship became substantially stronger in January and April 2021, after the end of the second and third phases of the JobKeeper program. This was particularly notable in less hard-hit industries, suggesting that by this point, as the economy had largely recovered, JobKeeper may have been supporting low productivity firms in less affected industries and thereby preventing efficient reallocation of resources (Figure A3). This provides some initial evidence that JobKeeper may have been influencing the relationship between productivity and growth, which we explore in more detail in the next section.

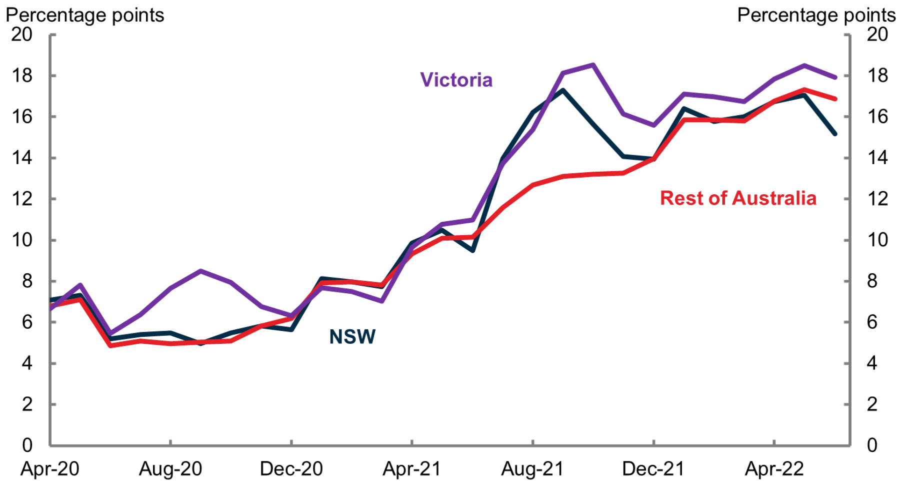

Figure 5. : Difference in performance between high and low productivity firms, by region

Notes: Lines show estimated difference in employment growth between high productivity firm (LP one standard deviation above industry mean - 1.25 log points) and a low productivity firm (LP one standard deviation below industry mean).
Source: Authors' calculations based on administrative STP and BIT data (Australian Tax Office 2020A, 2020B, 2021A).

D. Robustness

The baseline results are robust to a range of tests, as outlined in Appendix B. These include: i) using a turnover-based measure of labour productivity instead of value-added sales to ensure firms with zero or negative value-added are not dropped from the sample (see Table B5);[16] ii) using an employment growth rate constructed from a headcount of employees with paid employment only, rather than all registered employees (see Table B6); and iii) using a measure of TFP constructed using the approach proposed in Ackerberg, Caves and Fraser (2015) (see Table B7). The TFP model can only be estimated for a smaller sample of companies that have been in operation for a number of years, and so is not our preferred approach.

IV. Productivity, reallocation and JobKeeper

A. Empirical framework

While the JobKeeper scheme was associated with a noticeable decline in the overall rate of job reallocation (i.e. "hibernation"), its impact on the reallocation-productivity nexus is less clear. Accordingly, we explore whether the efficiency of labour reallocation varies according to the usage of JobKeeper 1.0 at the local labour market level by estimating the following specification:

$$E_{isr} = \alpha_0 + \beta_1 LP_{isr} + \beta_2 LP_{isr} * JKsh_{sr} + \delta_1 LP_{isr} * Cycle_{sr} + \chi_{isr} + \rho_{sr} + \epsilon_{isr} \quad (3)$$

where E is cumulative change in employment between March and November 2020. All explanatory variables are identical to the baseline specification with two key exceptions. First, we include an interaction term between firm-level labour productivity (LP) and

[16]Coefficient estimates are slightly smaller though similar to our baseline model using turnover based labour productivity.

JKsh, which measures the share of employees in a 4-digit ANZSIC industry in a given state that received the JobKeeeper 1.0 subsidy.[17] If $\beta_2 > 0$ ($\beta_2 < 0$), then job reallocation was on average more (less) productivity-enhancing – and high productivity firms were more (less) resilient to the shock – in local labour markets with an above-average share of the workforce were covered by JobKeeper.[18] Second, given that receipt of the subsidy was a function of economic distress, we also include an interaction between LP and the state-industry specific business cycle (*Cycle*), proxied by the percentage change in employment at the (3-digit ANZSIC) industry-level within a given state since February 2020 (Australian Bureau of Statistics 2020B).[19] Standard errors are clustered at the state-industry level.

While equation 3 estimates how JobKeeper shaped the reallocation-productivity link on average over the first phase of the scheme, the effect of the policy may have changed over time, particularly given the strong recovery observed in Australia. To consider this, we exploit the fact that the scheme had multiple stages, and that firms had to re-qualify between the stages, as described in Section 1. Given the strong economic recovery underway in most sectors of the economy over the second half of 2020, the latter phases of JobKeeper protected a narrower subset of firms. This included firms in sectors that were still heavily affected by economic restrictions. It also potentially included firms that had simply been less adaptable to the economic consequences of the shock, along with firms that had been on a downward trajectory even prior to COVID-19. We can use this change in the conditions and JobKeeper coverage to try to understand how much productivity-enhancing reallocation the policy was holding back before it was wound down.

Specifically, we adapt equation 3 in two ways to explore the implications of the phasing-out of JobKeeper. First, we re-estimate the model where the dependent variable is the change in employment from March to May or August 2020 to estimate the implications of the JobKeeper 1.0 regime for the reallocation-productivity link over time. Second, to explore the implications of the transition from JobKeeper 1.0 to JobKeeper 2.0, we estimate the following specification:

$$E_{isr} = \alpha_0 + \gamma_1 LP_{isr} + \gamma_2 LP_{isr} * [JK1sh_{sr} - JK2sh_{sr}] + \delta_1 LP_{isr} * Cycle_{sr} + \chi_{isr} + \rho_{sr} + \epsilon_{isr} \tag{4}$$

where E is cumulative change in employment between September 2020 and November 2020 (the end of JobKeeper 1.0). The specification also includes an interaction term between firm-level labour productivity (LP) and $JK1sh - JK2sh$, which captures the change in the share of subsidised employment in a local labour market between JobKeeper 1.0 and JobKeeper 2.0. By construction, $JK1sh - JK2sh$ will be more positive in those industry-state cells that had fewer workers covered under JobKeeper 2.0, relative to under JobKeeper 1.0, and thus captures the extent to which the scheme was phased-out and labour was freed for reallocation. If $\gamma_2 > 0$, then productivity-enhancing reallocation was stronger in those local labour markets that had more of their workforce released from the scheme and thus potentially available to reallocate from less to more productive firms. We also estimate an alternate specification where we include $JK1sh$ and $JK2sh$ separately, which produces similar results. All other explanatory variables are identical to Equation

[17] 4-digit is the most fine-grained industry definition in the Australian ANZSIC classification, including industries such as Cafes and Restaurants (4511), and Takeaway Food Services (4512).

[18] We de-mean the *JKsh* term, so that β_1 in Equation 3 can be interpreted as the extent of productivity-enhancing reallocation for a local labour market with the (sample) average coverage of JobKeeper. We follow this de-meaning procedure for all subsequent interaction variables in the paper.

[19] The results are robust to using hours, rather than employment. Results available on request. 3-digit ANZSIC industries are the most fine-grained industry data available from public data at a state level.

3, though we allow the cycle variable to account for different overall market outcomes across the March to November, and August to November periods.

Finally, we use a similar specification to look at the end of the JobKeeper program, where the *JKsh* variable represents the share of subsidised employment in a local labour market on JobKeeper 2.2 (the final quarter of the program). In this regression, E is cumulative change in employment between March 2021 and May 2021. By construction, If $\gamma_2 > 0$, then productivity-enhancing reallocation was stronger in those local labour markets that had more of their workforce released from the scheme. All other explanatory variables are identical to above, though we again allow the cycle variable to account for different overall market outcomes across the March 2020 to May 2021, and March 2021 to May 2021 periods.

B. *JobKeeper results*

Column 1 of Table 3 shows the estimation results of Equation 3, where the dependent variable is the cumulative change in employment from March to November 2020.[20] The coefficient on productivity is again positive and significant, suggesting that in local labour markets with the (sample) average JobKeeper employment share, (within-industry) labour reallocation remained productivity-enhancing. The *LP*JKsh* interaction term is positive and statistically significant, even after controlling for the magnitude of the economic shock on the reallocation-productivity link at the state-industry level. This suggests that on average over the life of JobKeeper 1.0, those local labour markets that had a higher proportion of the workforce in receipt exhibited a stronger (within-industry) connection between labour reallocation and productivity. This provides further evidence in support of the notion of "hibernation, not zombification." However, it is possible that the effects of the policy changed over time.

Columns 2 and 3 explore the reallocation-productivity link under the JobKeeper 1.0 regime, where the dependent variable is the change in employment from March to August (Column 2) and to May (Column 3). In both cases, the coefficient on the *LP*JKsh* interaction term is positive and statistically significant but is somewhat larger than in Column 1. This suggests that JobKeeper may have become more distortive over time.

This assertion is supported by the results looking at the phase down from the JobKeeper 1.0 to JobKeeper 2.0 regime. Column 4 of Table 3 shows the estimation results of Equation 4. The *LP*[JK1sh - JK2sh]* interaction term is positive and statistically significant. This suggests that (within-industry) productivity-enhancing labour reallocation was stronger in those local labour markets that had more of their workforce released from JobKeeper 1.0 and available to reallocate from low to high productivity firms. Thus, it appears that the policy was becoming distortionary as the economy recovered – preventing labour from flowing to more productive firms – and that this distortion was partly removed with the phasing-down of the program after the first six months.

Similarly, Column 5 shows that the end of the program was associated with greater (within-industry) productivity-enhancing labour reallocation in those local labour markets that had more of their workforce released from JobKeeper 2.2. This is consistent with earlier evidence of a sharp increase in the coefficient from the baseline model around this time, particularly for those industries less affected by COVID-19, and suggests the policy was limiting some productivity-enhancing reallocation and supporting low-productivity firms in some industries towards its end. These results are largely robust to using TFP in place

[20]Note that for much of this section we end our regression periods in May, August or November. This is to align with the quarterly availability of detailed data on employment by industry and state, which we use as to control for the potential cyclically of reallocation.

of labour productivity (Appendix B Table B10).

Table 3—: Firm-level growth responsiveness to productivity: Role of JobKeeper

	(1) Mar-20 to Nov-20	(2) Mar-20 to Aug-20	(3) Mar-20 to May-20	(4) Sep-20 to Nov-20	(5) Mar-21 to May-21
Labour productivity	2.503	2.277	2.886	0.671	2.298
	(0.113)	(0.113)	(0.121)	(0.120)	(0.141)
Labour productivity x JK1 share	0.021	0.028	0.040		
	(0.006)	(0.006)	(0.006)		
Labour productivity x JK1 - JK2 share				0.027	
				(0.009)	
Labour productivity x JK2.2 share					0.029
					(0.012)
Labour productivity x Cycle1	-0.007	-0.022	-0.025	0.008	0.005
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Labour productivity x Cycle2				-0.004	
				(0.005)	
Labour productivity x Cycle 3					-0.003
					(0.006)
Age FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes	Yes
Industry x State FE	Yes	Yes	Yes	Yes	Yes
N	387,760	388,673	389,504	439,158	417,291
R-squared	0.024	0.032	0.070	0.024	0.045
Adjusted R-squared	0.018	0.025	0.064	0.019	0.040

Notes: Regressions are all variations of Equations (3) and (4). Standard errors clustered at the state*industry level. R-squared are overall R-squared. JK1 share, JK2 share, and JK 2.2 share denote share of state-industry workforce enrolled into JobKeeper 1, JobKeeper 2, and JobKeeper 2.2, respectively. JK1 - JK2 share denotes share enrolled into JobKeeper 1 minus the share in JobKeeper 2/2.2. Cyclical controls are change in industry-level employment from Feb-20 (Cycle 1), Aug-20 (Cycle 2), and Feb-21 (Cycle 3) to end dates used for dependant variables. Dependant variables are employment growth rates for periods detailed in table. Constant not shown.
Source: Authors' calculations based on administrative STP, JobKeeper and BIT data (Australian Tax Office 2020A, 2020B, 2021A, 2021B).

To illustrate the economic magnitude of these effects, Figure 6 simulates the difference in employment growth between a high and low productivity firm for various time periods, according to the share of local employment covered by JobKeeper, and across the regime's phases. The second panel shows that in a state-industry pairing where a high share of workforce (i.e. 60 per cent) was covered by JobKeeper 1.0, employment growth (over March and August 2020) was 7.2 percentage points higher in a high (versus low) productivity firm. This compares to an employment growth differential of around 4.1 percentage points in those parts of the economy where JobKeeper 1.0 had low coverage (i.e. 15 per cent of employees). This differential is even wider over the initial months of the pandemic (first panel).

The third panel of Figure 6 illustrates how differences in the extent to which JobKeeper 1.0 was phased-out in September 2020 shaped productivity-enhancing reallocation dynamics. In those parts of the economy where a large share of employment (i.e. 38 per cent) was released from JobKeeper, employment growth in high productivity firms was 2.9 percentage points higher than in low productivity firms, over September and November 2020. This compares to a meagre employment growth differential of just 0.5 percentage points in those state-industry cells where only a small share of employment (i.e. 7 per cent) was released from JobKeeper. Put differently, in those parts of the economy where little labour was released by the phase-down, there was virtually no productivity-enhancing labour reallocation.

The final panel of Figure 6 illustrates how differences in the extent to which JobKeeper was phased-out in March 2021 shaped subsequent productivity-enhancing reallocation dynamics. In those parts of the economy where a large share of employment (i.e. 17 per cent) was released from JobKeeper, employment growth in high productivity firms was 6.6 percentage points higher than in low productivity firms, over March to May 2021. This compares to 5 percentage points in those state-industry cells where only a small share of employment (i.e. 1.5 per cent) was released from JobKeeper.

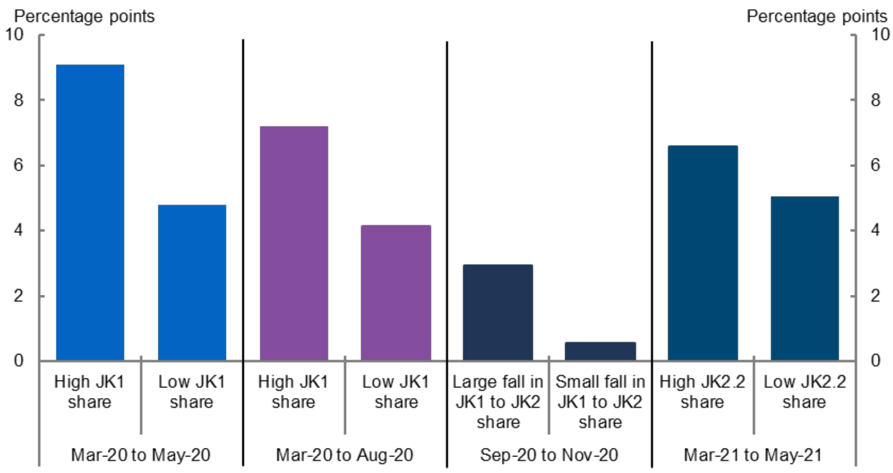

Figure 6. : Employment growth gap between high and low productivity firms, by JobKeeper uptake

Notes: High/low productivity firms are +/- one standard deviation from the mean of the productivity distribution, 1.25 log points. High JobKeeper 1 share is 60 per cent and low is 15 per cent. Large fall in JobKeeper share is 38 percentage points. Small fall is 7 percentage points. High JobKeeper 2.2 share is 17 per cent and low share is 1.5 per cent. These represent 10th and 90th percentiles of industry*state distribution.

Source: Authors' calculations based on administrative STP, JobKeeper and BIT data (Australian Tax Office 2020A, 2020B, 2021A, 2021B).

Before proceeding, the cyclical controls warrant discussion.[21] In Columns 2 and 3 of Table 2, the *LP*Cycle* interaction terms are negative and statistically significant, suggesting that labour reallocation was more productivity-enhancing in those local labour markets that experienced a larger decline in aggregate employment over the first six months of the pandemic (although this is less evident by November once much of the economic recovery had occurred).[22] This provides more direct evidence for the cleansing hypothesis, confirming the suggestive evidence outlined in Section 3.

One concern might be that we are picking up 'normal' seasonal patterns. While this is somewhat unlikely as it would require the seasonal patterns to be stronger for those sectors where labour is freed up at the end of each JobKeeper stage, it is still possible. To address this concern we run placebo tests for the above specifications. Specifically, we re-run the regressions shifting the employment growth variables and other controls forward one year, but keeping the original JobKeeper share values.

Table 4 shows the results. Focusing first on the JobKeeper 1 results, there is some marginally significant evidence that the productivity-growth nexus was stronger where JobKepeer 1.0 use was higher when focusing on growth from March 2021 to May 2021. [23] However the magnitude is much smaller compared to the 2020 regression, and does not have the same pattern of falling over time, suggesting the earlier results are not simply driven by seasonality.

Focusing on the roll off regressions, the relationship between growth and productivity from September 2021 to November 2021 was not stronger in local labour markets where more labour was freed up in the transition from JobKeeper 1 to JobKeeper 2 in September 2020. As such, it does not appear that the earlier finding was driven by seasonal patterns. The same cannot be said for the March 2022 to May 2022 period and JobKeeper 2.2.And while the evidence in this placebo test is less significant compared to the original regression (t-statistic of 2.0 compared to 2.5), we cannot rule out the the findings for the end of JobKeeper reflect normal seasonal patterns.

Taken together these results still suggest that JobKeeper initially strengthened the relationship between productivity and growth, and became more distortive over time. This was particularly evident at the end of the first phase when around two million individuals moved off the program, though the evidence is weaker for the end of the program when around one million individuals moved off. [24].

[21]These cyclical variables are unaffected by the exclusion of the JobKeeper share variable. This indicates that multi-collinearity is not an issue, and that we have enough variation to separately identify both the cyclical and JobKeeper effects. These results are available on request.

[22]Note that this is not the case in Columns 4 and 5. This is not surprising, given this focuses on outcomes over a much shorter period that is more distant from the peak of the crisis.

[23]In part, the significant relationship for this period could reflect a correlation between JobKeeper 1 shares, and JobKeeper 2.2 shares, with the final phase of the policy ending during this window.

[24]These numbers may understate the differences in the number of employees rolling off the program across the two periods. This is because the numbers quoted will include some business owners that were classified as eligible business participants, but who will not be included in our employment data. The share of these business owners rose as the program moved to later phases, alongside the observed increase in the share of micro businesses on the program

Table 4—: Firm-level growth responsiveness to productivity: Role of JobKeeper

	(1) Mar-21 to Nov-21	(2) Mar-21 to Aug-21	(3) Mar-21 to May-21	(4) Sep-21 to Nov-21	(5) Mar-22 to May-22
Labour productivity	3.937	4.155	2.033	-0.379	1.762
	(0.146)	(0.162)	(0.164)	(0.147)	(0.162)
Labour productivity	0.0156	0.0152	0.0152		
x JK1 share	(0.011)	(0.010)	(0.008)		
Labour productivity				0.011	
x JK1 - JK2 share				(0.011)	
Labour productivity					0.035
x JK2.2 share					(0.017)
Labour productivity	-0.008	-0.002	-0.002	0.011	0.001
x Cycle1	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Labour productivity				-0.015	
x Cycle2				(0.006)	
Labour productivity					-0.003
x Cycle 3					(0.006)
Age FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes	Yes
Industry x State FE	Yes	Yes	Yes	Yes	Yes
N	459,907	457,235	437,811	439,158	417,291
R-squared	0.016	0.028	0.036	0.024	0.045
Adjusted R-squared	0.010	0.023	0.030	0.019	0.040

Notes: Regressions are all variations of Equations (3) and (4). Standard errors clustered at the state*industry level. R-squared are overall R-squared. JK1 share, JK2 share, and JK 2.2 share denote share of state-industry workforce enrolled into JobKeeper 1, JobKeeper 2, and JobKeeper 2.2, respectively. JK1 - JK2 share denotes share enrolled into JobKeeper 1 minus the share in JobKeeper 2/2.2. Cyclical controls are change in industry-level employment from Feb-20 (Cycle 1), Aug-20 (Cycle 2), and Feb-21 (Cycle 3) to end dates used for dependant variables. Dependant variables are employment growth rates for periods detailed in table. Constant not shown.
Source: Authors' calculations based on administrative STP, JobKeeper and BIT data (Australian Tax Office 2020A, 2020B, 2021A, 2021B).

Our results do not imply that the latter phases of the JobKeeper scheme were not warranted. A number of sectors were still heavily affected by pandemic-induced restrictions, particularly in Victoria, and thus some policy support was necessary. The policy also had additional aims, including supporting worker incomes alongside welfare payments, and reducing uncertainty (Australian Government 2020). However, it highlights the fact that job retention schemes are likely to become more distortive over time, underscoring the need to phase-out such schemes where possible – which is what exactly occurred in the case of JobKeeper.

V. Which firms took-up the JobKeeper subsidy?

Why was the reallocation-productivity link stronger in those parts of the economy that were initially more shielded by JobKeeper? And why did policy shift from supportive to distortive over time? One possible explanation lies in the characteristics of the firms that took-up the retention scheme, and how this changed between the two phases of the scheme. The zombification hypothesis assumes that less productive firms are more likely to receive government support, which in turn crowds-out growth opportunities for more productive firms. We thus consider productivity differences between subsidised and non-subsidised firms, as well as the relative propensity of productive but financially fragile firms to utilise the scheme.

A. *Empirical framework*

To explore these mechanisms, we estimate linear probability models of the form:

$$JK_{isr} = \alpha_0 + \varphi_1 LP_{isr} + \varphi_2 FC_{isr} + \chi_{isr} + \rho_{sr} + \epsilon_{isr} \tag{5}$$

where JK is a dummy variable that equals one if a firm is a recipient of the JobKeeper subsidy, zero otherwise, with separate models run for each regime (i.e. JobKeeper 1.0 and JobKeeper 2.0). LP is firm-level labour productivity. FC are various indicators of financial constraints that would leave a firm particularly exposed to the shock.[25] First, we include a dummy variable that equals one if a firm has insufficient liquid assets (i.e. cash reserves) to cover six months' worth of expenses (based on 2018-19 BIT data). Second, we include a variable that captures the share of the firm's expenses that are 'fixed' (rent, leases and interest costs based on 2018-19 BIT data). The latter term is included since fixed costs are still incurred during pandemic-induced disruptions to commercial activity and thus firms with a high share of fixed costs may be more likely to apply for JobKeeper. χ includes dummies for firm size and age classes, as defined in the baseline model in Section 3, and the wage share of total expenses. Finally, the model includes interacted industry and state fixed effects, such that we are identifying how participation in JobKeeper is related to differences in firm productivity within narrowly defined sectors, after controlling for state-level shocks.

The coefficients of interest are φ_1 and φ_2. If $\varphi_1 > 0$ and $\varphi_2 > 0$, then the JobKeeper subsidy was taken up by more productive firms on average, as well as by financially constrained firms, suggesting that JobKeeper worked as an effective crisis tool to shield the productive fabric of the economy. By contrast, if $\varphi_1 < 0$, then less productive firms were more likely to take-up the subsidy, lending more credence to the zombification hypothesis. Changes in these coefficients over time will also provide further insights into changes in the effects of the policy over time.

[25] For some discussion of the role of liquidity constraints during COVID, see for example OECD (2020).

B. Empirical results

Table 5 shows the estimation results of Equation 5. Separate linear probability models are estimated for the two policy regimes. Overall, high productivity firms were significantly more likely than low productivity firms to take-up the subsidy under JobKeeper 1.0, but this was not the case under JobKeeper 2.0.

The coefficient on labour productivity in Column 1 is positive and statistically significant at the 1 per cent level. This suggest that within industries, more productive firms were more likely to participate in JobKeeper 1.0, after accounting for a firm's size, age and state. This result remains after controlling for the state of firm's pre-pandemic balance sheet (Column 2), which reveals a higher probability of JobKeeper take-up amongst firms that were illiquid or had a high share of fixed costs in expenses. The latter is unsurprising given that the pandemic – and measures to curb the spread of the virus – shutdown commerce in some instances, which would have been more harmful for firms with limited cash reserves and that still had significant (fixed) costs to cover despite ramping down production. Column 3 shows that firms in the second, third and highest (within-industry) productivity quartiles were more likely to participate in JobKeeper 1.0, than firms in the least productive quartile. The economic magnitudes of these differences are moderate, with a firm one standard deviation below the mean of the (within-industry) productivity distribution being around 4-5 percentage points less likely to enrol in JobKeeper 1.0, compared to a firm one standard deviation above the mean.

These results are consistent with canonical models of firm dynamics (Hopenhayn 1992; Jovanovic 1982). When faced by uncertain future outcomes – and some fixed costs of operation – high productivity firms are likely to take on the cost and operate, given the higher expected value of doing so. So when all firms were faced with a broad-based and uncertain COVID-shock, more productive firms would have had more incentive to take-up the subsidy, given they see greater firm value in the medium-term.

Table 5—: Role of firm-level productivity and financial constraints in JobKeeper take-up

	(1) JK 1	(2) JK 1	(3) JK 1	(4) JK 2	(5) JK 2	(6) JK 2
Labour productivity	0.012	0.017		-0.011	-0.008	
	(0.002)	(0.002)		(0.002)	(0.002)	
Labour productivity Q2			0.076			0.015
			(0.004)			(0.004)
Labour productivity Q3			0.075			-0.002
			(0.006)			(0.004)
Labour productivity Q4			0.045			-0.022
			(0.006)			(0.004)
Fixed share of expenses		0.274	0.266		0.241	0.235
		(0.027)	(0.027)		(0.027)	(0.027)
Liquidity		0.052	0.045		0.017	0.014
		(0.003)	(0.003)		(0.002)	(0.002)
Wage share of expenses	No	Yes	Yes	No	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	284392	284392	284392	281105	281105	281105
R-squared	0.111	0.115	0.117	0.102	0.105	0.105
Adjusted R-squared	0.101	0.105	0.107	0.092	0.094	0.095

Notes: Regressions are all variations of Equations (5). Dependant variables are dummies which equal one if firm participates in JobKeeper. Standard errors clustered at the state*industry level. Labour productivity Q1 is the bottom quartile and is the base case. Fixed share of expenses denotes ratio of fixed (rent, leasing and interest) to total expenses. Liquidity is a dummy which equals 1 when current/liquid assets are insufficient to cover 6 months of expenses. Wage share of expenses is Yes when the ratio of wages to total expenses is controlled for in regression. Sample slightly different to baseline – includes some firms not in STP (e.g. due to late registrations for the system or becoming a non-employing business). Constant not shown.
Source: Authors' calculations based administrative JobKeeper and BIT data (Australian Tax Office 2020A, 2020B, 2021B).

Table 5 also shows that the characteristics of firms receiving JobKeeper 2.0 differ to those for JobKeeper 1.0. Specifically, the estimated coefficient on productivity is now negative and statistically significant (Columns 4 and 5). This suggest that within industries, less productive firms were more likely to participate in JobKeeper 2.0, with firms one standard deviation below the mean productivity level now being 2 percentage points more likely to enrol, compared to a firm above the mean.[26] This is consistent with a leftward shift in the productivity distribution of firms receiving JobKeeper 2.0, relative to JobKeeper 1.0 (Figure 7). Indeed, Column 6 of Table 5 shows that while firms in the second quartile was more likely to participate in JobKeeper 2.0 than firms in the least productive quartile, the economic magnitude of these differences are now small. And, firms in the most productive quartile were significantly less likely to participate in JobKeeper 2.0, than firms in the lowest productivity quartile.

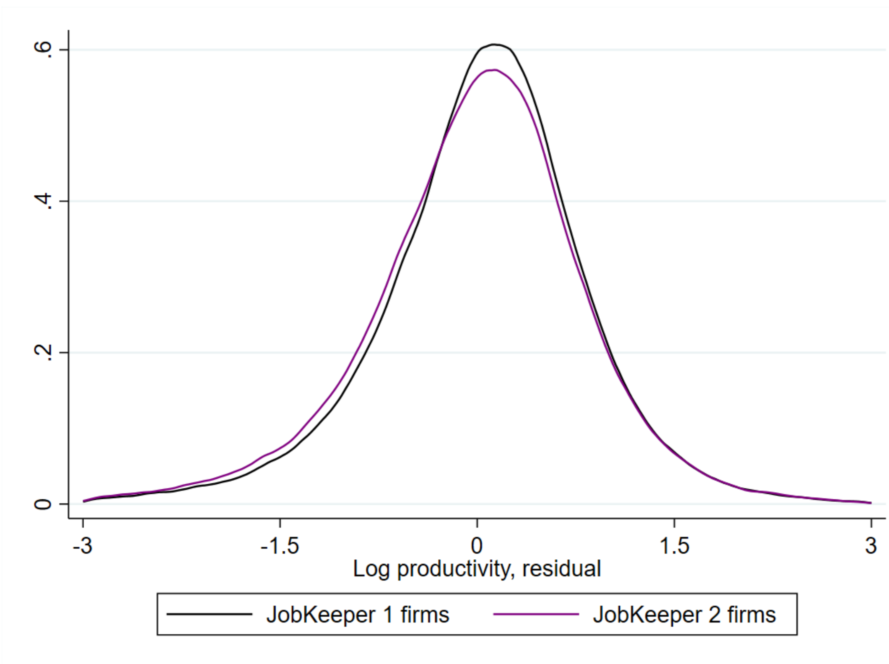

Figure 7. : Distribution of labour productivity for JobKeeper recipient firms

Notes: Plots residuals from regression of labour productivity on balance sheet controls from take-up regressions in Table 3. Residuals plotted separately for firms in JobKeeper 1.0 and 2.0.
Source: Authors' calculations based on administrative JobKeeper and BIT data (Australian Tax Office 2020A, 2020B, 2021B).

This finding for JobKeeper 2.0 is consistent with the above reallocation results, and with expectations, given the duration of the shock and economic recovery. By this stage, there were two broad groups of firms who were likely to qualify: i) those in sectors still heavily affected by restrictions; and ii) those firms who were either already on a downward trajectory – and so qualified for year-on-year turnover declines – or who had not adapted. The latter set of firms could generally be expected to be less productive. These firms may have otherwise exited via market selection, or had lower managerial and technological capability, which would have comprised their adaptability in light of the nature of the shock – i.e. one where being online and able to operate remotely were key (Andrews, Charlton & Moore 2021).

[26]If we exclude the balance sheet controls, we can include a broader sample that includes sole-trader unincorporated businesses, who do not report on their balance sheets. Doing so does not affect the JobKeeper 1.0 results. For JobKeeper 2.0, the coefficient on productivity turns from statistically negative, to statistically or economically indistinguishable from zero, depending on the specification. So, in this case, firms receiving JobKeeper 2.0 are no longer less productive, though they are not more productive. These results are available on request.

It also shows that many firms, particularly the productive ones, no longer needed the payment given the broader recovery. Without the phase-down of the scheme, these firms' hiring decisions would have continued to be distorted by JobKeeper. This highlights the idea that the allocative costs of crisis policies that prioritise preservation over reallocation build over time, and justifies the gradual winding down of the JobKeeper scheme.

One potential concern regarding the results might be that positive correlation between JobKeeper take-up and firm-level productivity reflects the fact that short-tenure casual workers – i.e. those with less than 12 months of tenure – were ineligible for the JobKeeper subsidy. Moreover, modelled productivity may be lower for such firms, as they will have a higher modelled headcount, and thus lower labour productivity all else equal. To address this concern, we re-run the take-up model using measures of profitability – such as Return on Assets and a loss-maker dummy – that are not subject to the same measurement concern. When we do so we find that firms taking up JobKeeper 1.0 were more profitable, but those taking up JobKeeper 2.0 were not (see Table B11), consistent with the baseline productivity results.

VI. Aggregate implications

How important was it for aggregate labour productivity that job reallocation and firm productivity remained connected over the course of the pandemic? To address this question, we follow Decker et al. (2020) and exploit the following identity to create indexes of aggregate labour productivity (P):

$$P_t = \sum_i s_{it} p_{it} \tag{6}$$

where: s and p are the employment share and (log) labour productivity level of each firm i. We combine actual realisations of firm-level labour productivity with the implied predicted employment shares from the earlier estimated models over 2020 for three counterfactual policy scenarios.

First, we estimate how much higher aggregate labour productivity was due to the connection between employment growth and (lagged) firm-level productivity demonstrated in Table 2 (Column 1), compared to a counterfactual scenario where the pandemic completely severed the link between reallocation and productivity (i.e. $\beta = 0$ in Equation 2). Under this counterfactual, each firm – within industry, state, firm size and age classes – has the same employment growth, and therefore no change in their employment share (s), regardless of their productivity level (p). We do this over the sample to December 2020, rather than to May 2021, given the economy had largely recovered by early 2021 and health restrictions were employed less frequently. We also estimate the simulation over a shorter sample to August 2020 to compare to the second exercise.

Second, we estimate the increase in productivity stemming from the boost to the reallocation-productivity nexus associated with JobKeeper 1.0. Mechanically this involves using the coefficients in Column 2 of Table 3 to compare the outcomes with the actual reach of JobKeeper 1.0 (*JKsh*=actual), relative to a scenario where JobKeeper was never introduced (*JKsh*=0). This can also be thought of as considering a counterfactual where JobKeeper uptake was not correlated with firm productivity, and so provided no boost to the reallocation-productivity nexus ($\beta_2 = 0$) in Equation 3.

Third, we estimate how much lower aggregate labour productivity would have been if the share of workers covered by JobKeeper 2.0 in each state-industry cell was identical to JobKeeper 1.0 (JK1sh - JK2sh = 0), based on the coefficients in Column 4 of Table 3. This is akin to a scenario were JobKeeper was not phased out from late September 2020.

Finally, we estimate how much lower aggregate labour productivity would have been if no workers flowed off JobKeeper 2.2, based on the coefficients in Column 5 of Table 3. This is akin to a scenario where JobKeeper was never ended in late March 2021.

In each case, the employment share prediction for a firm in *t+1* applies the model's prediction of employment growth in *t+1* to the (initial) level of employment for the firm in *t*. We then construct two indexes of aggregate productivity (P) – the actual and counterfactual – for each scenario outlined above and their difference yields the aggregate impact:

$$P_{t+1}^{Gain} = \sum_{i} (s_{i,t+1}^{Actual} - s_{i,t+1}^{Counterfactual}) P_{it} \tag{7}$$

Figure 8 illustrates the results for each scenario. First, the greater resilience of high productivity firms to the pandemic raised aggregate labour productivity by an estimated 5.2 per cent using the baseline model, relative to a counterfactual where the pandemic completely severed the reallocation-productivity link (Bar 1a: Distorted reallocation). The estimate is slightly smaller at 4.3 per cent if we use the JobKeeper 1.0 model and a shorter sample to August 2020 to run the same counterfactual (Bar 1b: Distorted reallocation JK specification). In this case, the estimate is more directly comparable to the JobKeeper 1.0 result below, as it uses the same model specification and period, and so better allows us to consider the 'share' of the boost related to JobKeeper.

Second, the introduction of the JobKeeper scheme – and more specifically the tendency for JobKeeper 1.0 to disproportionately shield higher productivity firms, thus strengthening the reallocation-link – boosted aggregate labour productivity by an estimated 2.6 per cent. This represents a bit over half of the estimated boost to labour productivity stemming from the reallocation-productivity link (Bar 2a: JK never introduced). The corollary is that without the JobKeeper scheme, there would have been more of an indiscriminate shakeout (via contraction or exit) of high productivity – and especially productive but liquidity constrained – firms, imparting significant scarring effects on the economy's productive fabric.

Finally, if policymakers did not adjust the JobKeeper scheme from late September 2020, aggregate labour productivity would have been an estimated 1.5 per cent lower in November 2020, reflecting the increasing allocative distortions of JobKeeper over time (Bar 2b: JK 1.0 not phased out). This implies significant aggregate gains from the phase-out of the scheme, although these gains may be temporary in the sense that some adjustment would have invariably occurred when the policy was removed. Further, productivity would have been around 0.6 per cent lower in May 2021 had the final stage of JobKeeper not been removed in late March 2021 (Bar 2c: JK 2.2 not phased out), though as noted above, the findings of a boost in reallocation at the end of JobKeeper are less convincing.

VII. Conclusion

This paper finds that while job reallocation fell following the onset of the pandemic, a non-trivial share of firms were still adding and shedding workers. Moreover, this reallocation process remained linked to productivity: high productivity firms were more likely to expand and low productivity firms remained more likely to contract or exit. While this link appears to have strengthened in the early, acute phase of COVID-19, overall the relationship appears to have weakened significantly over much of 2020/21 compared to the pre-COVID period. This suggests that the pandemic may carry some consequences for medium-term productivity growth in Australia via the reallocation channel, though the strengthening of the link over late 2021 provide some comfort.

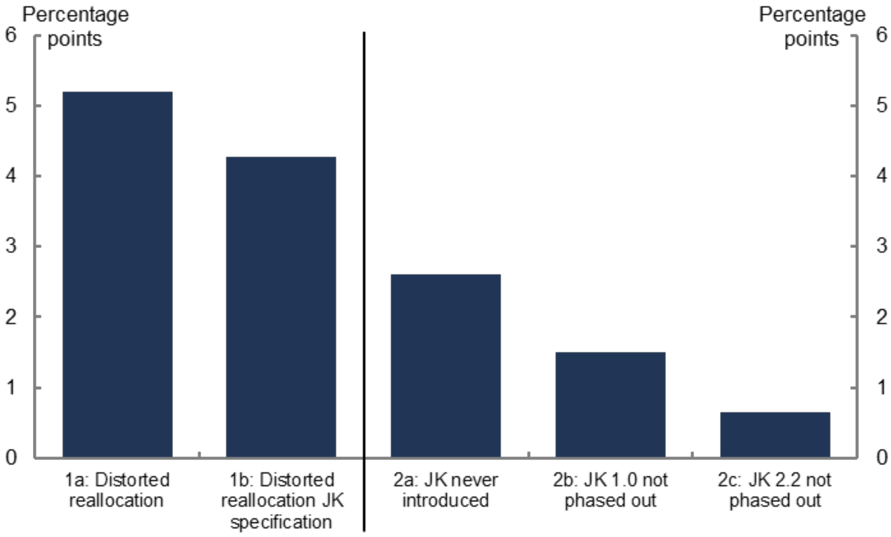

Figure 8. : Gain to aggregate labour productivity relative to counterfactual scenarios

Notes: Charts difference in aggregate productivity using predicted employment outcomes, and counterfactual scenarios discussed above. Bar 1a is based on baseline model results in Table 1 Column (1), but estimated to December 2020. Bar 1b is based on results in Table 2 Column (2), estimated to August. As such, it is more comparable to the results in Bar 2a, which uses the same model but focuses on the JobKeeper term. Bar 2b uses the model in Table 2 Column (4) estimated from August to November 2020. Bar 2c uses the model in Table 2 Column (6) estimated from August to November.
Source: Authors' calculations based on administrative STP, JobKeeper and BIT data (Australian Tax Office 2020A, 2020B, 2021A, 2021B).

While our paper represents the first evidence of the impact of the pandemic on reallocation-productivity link using comprehensive administrative data, we also contribute to the ongoing policy debate of the costs and benefits of job retention (or wage subsidy) schemes. Under the first phase of the JobKeeper scheme – which provided broad-based crisis support from late March to September 2020 – we show high productivity firms were more likely to take-up JobKeeper. Moreover, the scheme disproportionately shielded productive but financially fragile firms – a pivotal group who's pre-mature exit or downsizing is a key mechanism through which recessions can impart scarring effects. One consequence was that productivity-enhancing reallocation was actually stronger in those local labour markets that had a higher proportion of workforce in receipt of JobKeeper. However the scheme appears to have become more distortive over time, impinging on the reallocation-productivity link by preventing reallocation of resources from less to more productive firms.

Policies aimed at preserving links between workers and firms during the crisis phase can potentially protect workers from scarring without significantly distorting the firm dynamics of the economy. While this suggests concerns over job retention schemes leading to zombification were overplayed, our results also demonstrate that there is a fine line between such policies being supportive and distortive. This paper highlights the need for such crisis policies to be truly temporary and for their design to evolve as economic conditions change.

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For Online Publication - Appendix A: Additional Figures

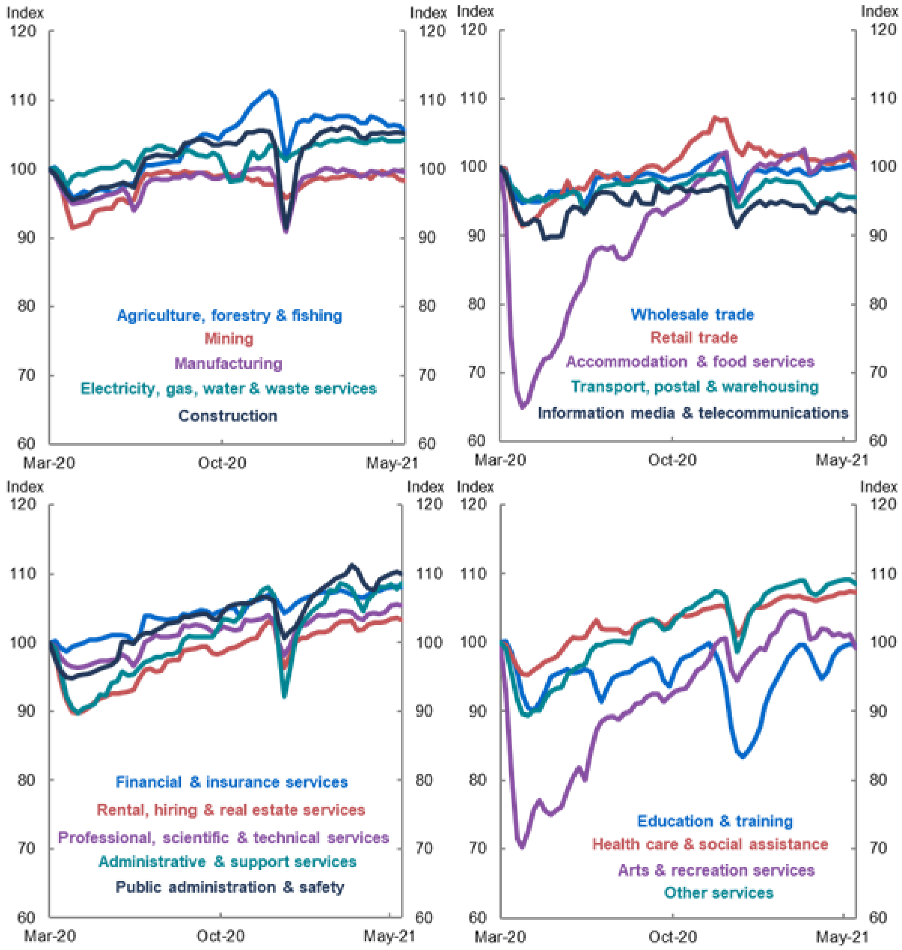
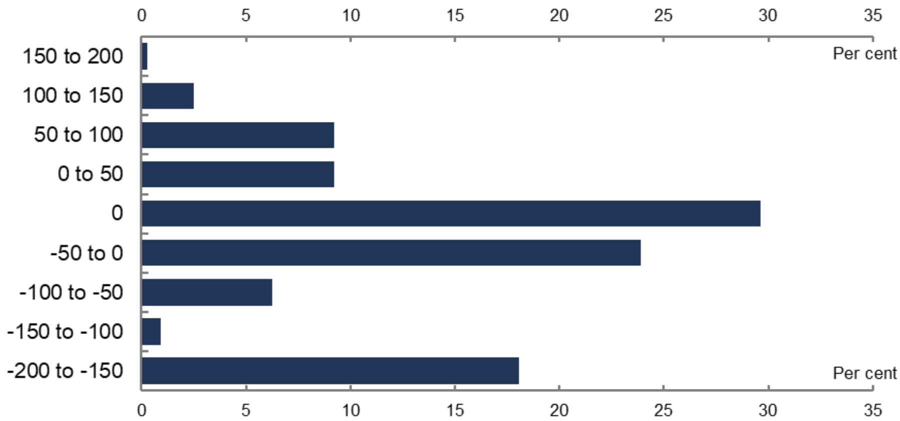


Figure A1. : Payroll jobs by division

Notes: Payroll jobs by division, indexed to week ending 14 March 2020.
Source: Australian Bureau of Statistics (ABS) Weekly Payroll Jobs and Wages in Australia, Week ending Saturday 11 September 2021.

(a) Distribution of employment growth in STP



(b) Distribution of value added per worker

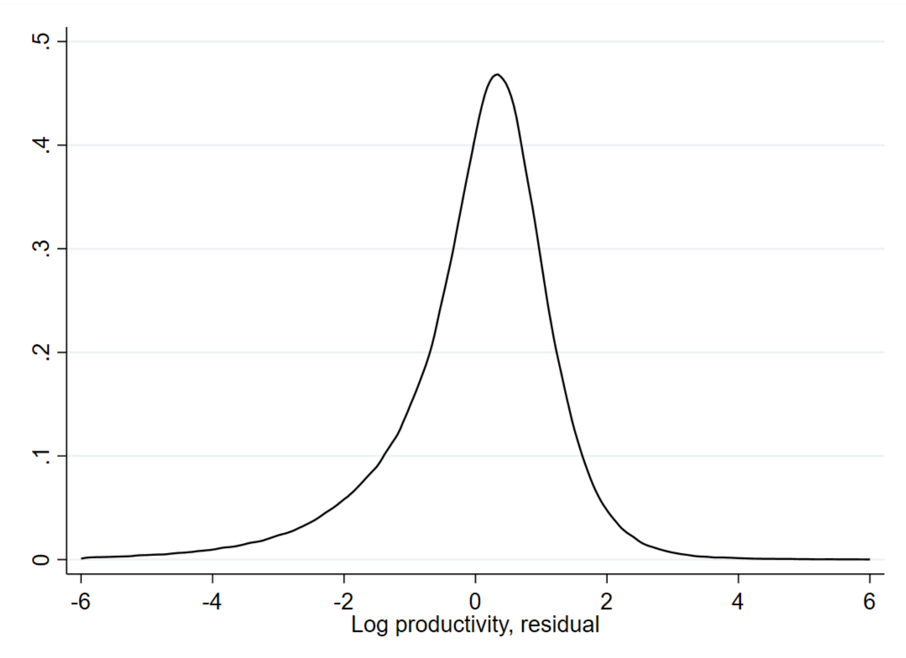


Figure A2. : Widespread heterogeneity in firm performance

Notes: Panel (a) shows the distribution of employment growth from March to May 2021 in STP. Panel (b) plots the average of the within-industry productivity distributions, based on the residuals of a regression of log value added per worker on 4-digit industry dummies.
Source: Authors' calculations based on STP and BIT data.

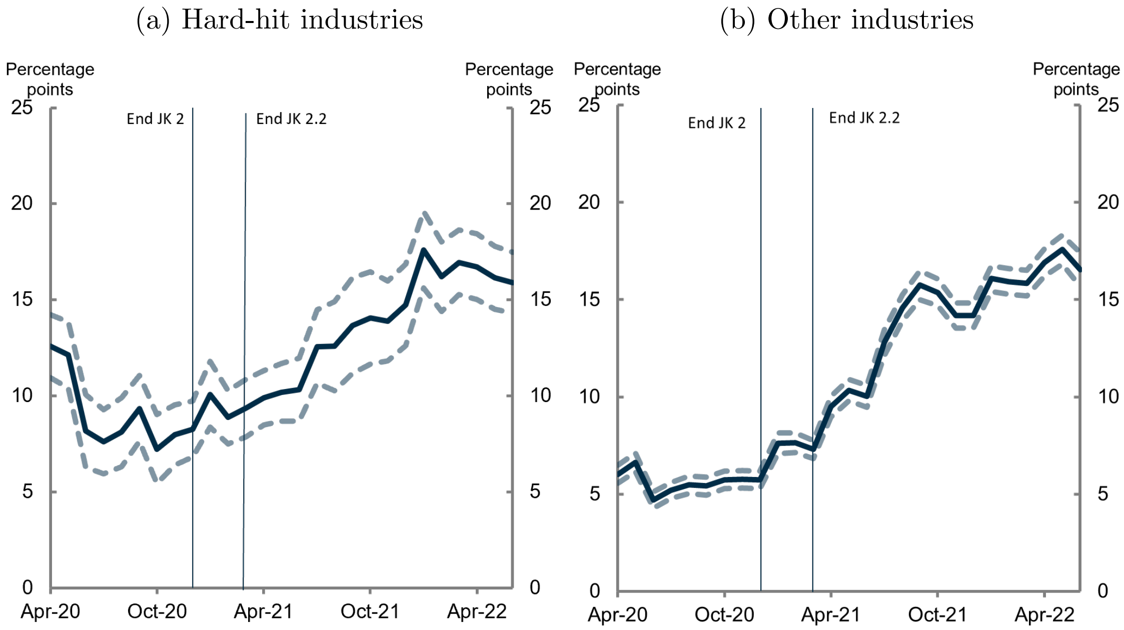


Figure A3. : Difference in performance between high and low productivity firms, by industry

Notes: Solid lines show estimated difference in employment growth between high productivity firm (LP one standard deviation above industry mean) and a low productivity firm (LP one standard deviation below industry mean). Dashed lines denote 90 percent confidence intervals. Based on specification in Table 1 Column (1) run for different periods. Hard-hit industries are Accommodation and Food Services, and Arts and Recreation Services.
Source: Authors' calculations based on STP and BIT data.

For Online Publication - Appendix B: Additional Tables

Table B1—: Distribution of jobs by division

	(1) Labour Account	(2) STP
Agriculture, Forestry and Fishing	3.3	1.3
Mining	1.3	1.7
Manufacturing	6.4	6.7
Electricity, Gas, Water and Waste Services	0.9	1.0
Construction	8.2	6.5
Wholesale Trade	4.2	4.5
Retail Trade	9.9	10.0
Accommodation and Food Services	7.3	6.4
Transport, Postal and Warehousing	4.3	3.9
Information Media and Telecommunications	1.2	1.3
Financial and Insurance Services	3.4	4.2
Rental, Hiring and Real Estate Services	1.9	2.1
Professional, Scientific and Technical Services	8.9	8.3
Administrative and Support Services	6.8	6.8
Public Administration and Safety	5.5	6.6
Education and Training	7.2	7.8
Health Care and Social Assistance	14.4	14.7
Arts and Recreation Services	1.4	1.6
Other Services	3.6	3.4

Notes: Share of total jobs by division.
Source: Australian Bureau of Statistics (ABS) Labour Account Australia, seasonally adjusted series, December 2020. Australian Bureau of Statistics (ABS) Weekly Payroll Jobs and Wages in Australia, March 2021.

Table B2—: Summary statistics

	(1) Employment growth	(2) Labour productivity	(3) Firm age	(4) Firm size
Mean	-23.6	10.4	12.8	16.1
Median	0.0	10.6	10.0	4.0
Standard deviation	78.3	1.25	10.4	324.6
25th percentile	-28.6	9.8	4.0	2.0
Minimum	-200	2.7	0.0	1.0
Maximum	198.8	21.4	46.0*	133.0*

Notes: Based on 404,001 firm-level observations. Employment growth is bounded between -200 and 200, based on the method in Equation 1. Employment growth is from March to May 2021. Labour productivity, firm age, and firm size is for 2018-19. Starred values are 99th percentile to avoid recognition risk.
Source: Authors' calculations based on STP and BIT data.

Table B3—: Role of firm size in reallocation-productivity link

	(1) Employment growth	(2) Probability of Exit
<=4 employees x Labour productivity	5.092 (0.229)	-0.023 (0.001)
5-19 employees x Labour productivity	4.194 (0.195)	-0.020 (0.001)
20-49 employees x Labour productivity	3.923 (0.304)	-0.017 (0.001)
50-199 employees x Labour productivity	2.895 (0.389)	-0.010 (0.001)
>=200 employees x Labour productivity	3.088 (0.817)	-0.013 (0.003)
Age x Size FE	Yes	Yes
Industry x State x Size FE	Yes	Yes
N	401936	401936
R-squared	0.063	0.083
Adjusted R-squared	0.041	0.061

Notes: Baseline model in Equation (2) with interaction by firm size group. Standard errors clustered at the state*industry level. Dependant variable in (1) is employment growth rate from March 2020 to May 2021. Dependant variable in (2) is dummy which equals one if firm has exited in May 2021. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B4—: Role of firm age in reallocation-productivity link

	(1) Employment growth	(2) Probability of Exit
<=2 years x Labour productivity	3.261	-0.016
	(0.365)	(0.002)
3-5 years x Labour productivity	4.599	-0.021
	(0.332)	(0.001)
6-10 years x Labour productivity	4.303	-0.016
	(0.287)	(0.001)
11-20 years x Labour productivity	5.028	-0.023
	(0.239)	(0.001)
>20 years x Labour productivity	4.338	-0.018
	(0.252)	(0.001)
Size x Age FE	Yes	Yes
Industry x State x Age FE	Yes	Yes
N	401985	401985
R-squared	0.070	0.089
Adjusted R-squared	0.044	0.064

Notes: Baseline model in Equation (2) with interaction by firm age group. Standard errors clustered at the state*industry level. Dependant variable in (1) is employment growth rate from March 2020 to May 2021. Dependant variable in (2) is dummy which equals one if firm has exited in May 2021. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B5—: Baseline results using turnover-based productivity

	(1) Employment growth	(2) Probability of Exit
Labour productivity	4.997	-0.021
	(0.181)	(0.001)
Age FE	Yes	Yes
Size FE	Yes	Yes
Industry x State FE	Yes	Yes
N	435454	435454
R-squared	0.049	0.071
Adjusted R-squared	0.042	0.064

Notes: Baseline model in Equation (2) using turnover-based productivity, instead of value-added. Standard errors clustered at the state*industry level. Dependant variable in (1) is employment growth rate from March 2020 to May 2021. Dependant variable in (2) is dummy which equals one if firm has exited in May 2021. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B6—: Baseline results using alternative headcount metric

	(1) Employment growth	(2) Probability of Exit
Labour productivity	4.364	-0.019
	(0.145)	(0.001)
Age FE	Yes	Yes
Size FE	Yes	Yes
Industry x State FE	Yes	Yes
N	401997	401997
R-squared	0.048	0.068
Adjusted R-squared	0.040	0.060

Notes: Baseline model in Equation (2) using an employment growth rate calculated from a headcount measure of paid employees only. Standard errors clustered at the state*industry level. Dependant variable in (1) is employment growth rate from March 2020 to May 2021. Dependant variable in (2) is dummy which equals one if firm has exited in May 2021. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B7—: Baseline results using Total Factor Productivity (TFP)

	(1) Growth	(2) Growth	(3) Exit	(4) Exit
TFP	3.095		-0.022	
	(0.587)		(0.003)	
TFP Q2		4.158		-0.019
		(0.499)		(0.002)
TFP Q3		5.376		-0.029
		(0.505)		(0.002)
TFP Q4		4.516		-0.029
		(0.525)		(0.002)
Age FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Industry x State FE	Yes	Yes	Yes	Yes
N	177231	177231	177231	177231
R-squared	0.036	0.037	0.048	0.049
Adjusted R-squared	0.029	0.029	0.041	0.042

Notes: Regressions are variations of baseline model in Equation (2) using a Total Factor Productivity measure of productivity, instead of labour productivity. Standard errors clustered at the state*industry level. TFP Q1 is the bottom quartile and is the base case. Dependant variable in (1)-(2) is employment growth rate from March 2020 to May 2021. Dependant variable in (3)-(4) is dummy which equals one if firm has exited in May 2021. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B8—: TFP results: Role of firm size in reallocation-productivity link

	(1) Employment growth	(2) Probability of Exit
<=4 employees x TFP	4.418	-0.030
	(1.083)	(0.005)
5-19 employees x TFP	2.880	-0.022
	(0.788)	(0.003)
20-49 employees x TFP	2.599	-0.012
	(1.352)	(0.006)
50-199 employees x TFP	-0.917	-0.004
	(1.523)	(0.006)
>=200 employees x TFP	-1.229	-0.010
	(2.245)	(0.006)
Age x Size FE	Yes	Yes
Industry x State x Size FE	Yes	Yes
N	176513	176513
R-squared	0.054	0.065
Adjusted R-squared	0.029	0.040

Notes: Regressions are same as those in Table B3 but using a Total Factor Productivity measure of productivity, instead of labour productivity. Standard errors clustered at the state*industry level. Dependant variable in (1) is employment growth rate from March 2020 to May 2021. Dependant variable in (2) is dummy which equals one if firm has exited in May 2021. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B9—: TFP results: Role of firm age in reallocation-productivity link

	(1) Employment growth	(2) Probability of Exit
<=2 years x TFP	-3.234	0.009
	(4.653)	(0.019)
3-5 years x TFP	2.302	-0.024
	(1.407)	(0.006)
6-10 years x TFP	2.564	-0.018
	(1.098)	(0.005)
11-20 years x TFP	3.215	-0.022
	(0.799)	(0.004)
> 20 years x TFP	4.761	-0.028
	(1.032)	(0.004)
Size x Age FE	Yes	Yes
Industry x State x Age FE	Yes	Yes
N	176495	176495
R-squared	0.056	0.067
Adjusted R-squared	0.030	0.041

Notes: Regressions are same as those in Table B4 but using a Total Factor Productivity measure of productivity, instead of labour productivity. Standard errors clustered at the state*industry level. Dependant variable in (1) is employment growth rate from March 2020 to May 2021. Dependant variable in (2) is dummy which equals one if firm has exited in May 2021. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B10—: TFP results: Role of JobKeeper in reallocation-productivity link

	(1) Mar-20 to Nov-20	(2) Mar-20 to Aug-20	(3) Mar-20 to May-20	(4) Sep-20 to Nov-20	(5) Sep-20 to Nov-20	(6) Mar-21 to May-21
Labour productivity	2.225	2.152	2.499	1.172	1.171	3.436
	(0.180)	(0.166)	(0.157)	(0.168)	(0.168)	(0.214)
Labour productivity x JK1 share	0.011	0.021	0.037		0.056	
	(0.010)	(0.010)	(0.010)		(0.015)	
Labour productivity x JK1 - JK2 share				0.056		
				(0.015)		
Labour productivity x JK2 share					-0.061	
					(0.018)	
Labour productivity x JK2.2 share						0.063
						(0.022)
Labour productivity x Cycle1	-0.011	-0.027	-0.035	0.002	0.002	0.002
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Labour productivity x Cycle2				0.005	0.005	
				(0.007)	(0.007)	
Labour productivity x Cycle 3						-0.003
						(0.008)
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	163357	163750	163634	178074	178074	171843
R-squared	0.023	0.037	0.087	0.026	0.026	0.052
Adjusted R-squared	0.016	0.030	0.080	0.020	0.020	0.046

Notes: Regressions are same as those in Table 2 but using a Total Factor Productivity measure of productivity, instead of labour productivity. Standard errors clustered at the state*industry level. Constant not shown.
Source: Authors' calculations based on STP and BIT data.

Table B11—: JobKeeper scheme take-up and profitability

	(1) JK 1	(2) JK 1	(3) JK 2	(4) JK 2
ROA	0.022		-0.019	
	(0.004)		(0.003)	
Loss		-0.010		0.012
		(0.003)		(0.002)
Fixed share of expenses	0.211	0.170	0.220	0.184
	(0.023)	(0.020)	(0.024)	(0.021)
Liquidity	0.060	0.051	0.023	0.020
	(0.003)	(0.003)	(0.002)	(0.002)
	(0.003)	(0.003)	(0.002)	(0.002)
Wage share of expenses	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Industry x State FE	Yes	Yes	Yes	Yes
N	355361	402381	351169	397686
R-squared	0.121	0.114	0.102	0.095
Adjusted R-squared	0.113	0.106	0.093	0.087

Notes: Dependant variables are dummies which equal one if firm participates in JobKeeper. Standard errors clustered at the state*industry level. ROA defined as earnings before interest and tax (EBIT), divided by assets. Loss is a dummy which equals 1 if the firm has negative EBIT. Fixed share of expenses denotes ratio of fixed (rent, leasing and interest) to total expenses. Liquidity is a dummy which equals 1 when the firms does not have enough current/liquid assets to meet 6 months of expenses. Wage share of expenses is Yes when ratio of wages to total expenses is controlled for in regression. Sample slightly different to baseline – includes some firms not in STP (e.g. due to late registrations for the system or becoming a non-employing business). Constant not shown.
Source: Authors' calculations based on BIT data.