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Do Monetary Policy and Economic Conditions Impact Innovation? Evidence from Australian Administrative Data

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Abstract

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Keywords

innovation, monetary policy, firm-level data

JEL Classification

E32, E52, G32, O30

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Do Monetary Policy and Economic Conditions Impact Innovation? Evidence from Australian Administrative Data

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This paper examines whether monetary policy and economic conditions affect innovative activity and productivity in Australia, a small open economy that tends to import innovation from overseas. Most interestingly, United States monetary policy spills over and affects Australian firms' innovation. Within Australia, contractionary monetary policy reduces aggregate R&D spending and this leads to reduced productivity growth. However, using firm-level data and a survey measure of innovation that also captures adoption, we find heterogenous responses across different firm types. Small firms decrease innovation in response to contractionary monetary policy shocks whereas large firms increase innovation. This heterogeneity appears to reflect differing exposures to the demand and financial constraint channels of monetary policy. Overall, our results suggest that monetary policy and economic conditions have medium-run effects on productivity, though the effects are more heterogeneous than previously documented.

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1. Introduction

Productivity growth is the key determinant of living standards over the long term. Many factors can influence how quicky productivity grows, including technological change, competition, skilled labour, regulation, trade and tax policy (Aghion and Howitt 2008). But economists have traditionally assumed that productivity is unaffected by 'cyclical' factors such as current economic conditions and monetary policy, at least over the medium term.

More recently, though, there is a growing literature questioning this assumption. One stream of this literature argues that weaker economic conditions, particularly economic downturns, can lead to slower rates of innovation and technology adoption by businesses, which can in turn lead to persistent changes in productivity and economic output. These hysteresis effects are considered in Stadler (1990), Comin and Gertler (2006), Anzoátegui et al. (2019), Bianchi, Kung and Morales (2019) and Amador (2022) among others.

In a similar vein, there is evidence that contractionary monetary policy, which weakens economic conditions, can slow innovation and technology adoption, and therefore have persistent effects on productivity (Moran and Queralto 2018; Jordà, Singh and Taylor 2020; Ma 2023; Ma and Zimmerman 2023).[1] While the effects of expansionary and contractionary monetary policy are likely to cancel out over a cycle, such a finding highlights the potential for medium-run economic scarring to occur if policy is constrained by the effective lower bound on interest rates and therefore cannot offset economic downturns.

This has important implications for macroeconomic policy, but there is little evidence on these questions outside the US. Effects could differ substantially in a small open economy like Australia that imports innovation, compared to a large economy like the US that pushes the technological frontier. In addition to a US focus, much of the evidence to date has focused on narrow measures of innovative activity like R&D spending and patenting. These measures are likely to miss a large amount of innovative activity for counties such as Australia through adoption of existing technologies and processes. Empirically, adoption is an important determinant of aggregate productivity growth (OECD 2015; Majeed et al. 2021; Argente et al. 2020) and features in theoretical models of the effect of monetary policy on productivity (Moran and Queralto 2018). Finally, small open economics could also be affected by monetary policy shocks in larger countries such as the US.

The main contribution of this paper is to explore these issues. The most novel finding of the paper is that US monetary policy shocks negatively impact the innovative activity of Australian firms. The effect is strongest for exporters.

We begin our investigation by providing new evidence for Australia, a small open economy. We explore the effect of domestic monetary policy shocks on various measures of innovation, including measures that capture adoption of innovation developed elsewhere. Further, we explore whether effects differ by firm size and other characteristics, using firm-level information on innovation and adoption. As well as providing interesting insights into the heterogenous effects of monetary policy, this helps us to better understand the mechanisms through which monetary policy, and economic conditions, affect innovation. We explore two channels: weaker demand, which lowers incentives to

1 Baqaee, Farhi and Sangani (Forthcoming) propose a different mechanism whereby contractionary shocks lead to a reallocation of resources towards lower productivity firms.

innovate; and tighter credit conditions, which makes it harder to finance investment and innovation. We find that both are important. We find that contractionary monetary policy shocks reduce aggregate R&D spending and that changes in R&D spending have medium-run effects on productivity. However, we do not find any effect of monetary policy shocks on the number of patents filed, consistent with Australia being an importer of new-to-world innovations rather than a producer (Majeed and Breunig 2022).

From the firm-level analysis, we find that monetary policy shocks appear to have relatively little effect on the average of broader survey measures of innovation and adoption. But this result hides offsetting impacts of monetary policy by firm size. Following a contractionary policy shock the share of small and medium enterprises (SMEs) innovating declines, while the share of large firms innovating increases. These heterogeneous responses appear consistent with SMEs and large firms having differing exposure to the channels though which monetary policy affects innovation. Monetary policy tends to weigh on innovative activity by tightening credit constraints (the credit constraint channel), particularly for smaller firms. Monetary policy also weighs on innovation by lowering domestic demand (the demand channel) and exporting firms, who tend to be larger and who appear less exposed to this channel.

We then consider the effect of US monetary policy shocks, potentially important for a small open economy like Australia, both because of standard spillovers from US policy to domestic conditions (e.g. Georgiadis 2016; Kearns, Schrimpf and Xia 2022), and because Australia imports innovation from the US and US policy affects US innovative activity. We find spillovers from shocks to US monetary policy, but which work in the opposite direction. US monetary policy shocks negatively impact the innovative activity of exporters who are more exposed to international conditions.

Overall, our results suggest that monetary policy and economic activity can have medium-run effects on innovation and therefore productivity, though they paint a more complex and heterogenous picture compared to previous work. These effects are likely to cancel out over the cycle. However, the results reinforce the importance of using macro stabilisation policy to avoid sharp economic downturns, given the potential for medium-run economic scarring, whilst also highlighting the costs of having such policy constrained (Benigno and Fornaro 2018; Ikeda and Kurozumi 2019; Barlevy 2004; Garga and Singh 2021). The potential for monetary policy to affect innovation and productivity in the medium-run may slightly alter the trade-offs between stabilisation of output and inflation when faced with a supply shock, particularly if inflation expectations can be kept anchored (Fornaro and Wolf 2023; Queralto 2022). That said, the results do not suggest that central banks should focus mainly on output growth at the expense of inflation stabilisation given the risks of expectations de-anchoring, which could require a much larger response and a correspondingly sharper economic downturn.

This paper proceeds as follows. We first discuss the relevant literature on the determinants of innovation in Section 2 before giving an overview of our data and methodology in Section 3. We then look at the effects of monetary policy shocks on aggregate innovative activity – patents, trademarks and R&D – and firm-level innovation in Section 4, before exploring the channels though which monetary policy may affect innovation in Section 5. We then consider the aggregate effect of changes in R&D spending on productivity in Section 6 before concluding.

2. Literature review

Until recently, the prevailing wisdom was that current macro-economic conditions and monetary policy have no effect on productivity over the medium term. For monetary policy, this assumption is reflected in its so called 'neutrality'. However, a growing number of papers have begun to question this assumption, contributing to the broader literature on hysteresis. Much of this literature focuses on medium-run employment effects, due for example to labour market scarring for workers (e.g., Blanchard and Summers 1986; Ball 2009; Andrews et al. 2020), or changes in the nature and number of start-ups (Sedláček and Sterk 2021; Ouyang 2009; Davis and Haltiwanger 2021).

More recently the scarring literature has examined the medium-run implications for productivity, building on the existing evidence that economic and financial conditions can influence the amount of innovative activity undertaken (e.g., Brown, Fazzari and Petersen 2009; Ouyang 2011; Huber 2018; Webster and Jensen 2009). Early papers in this productivity hysteresis literature focused on economic downturns, and whether they could contribute to lower productivity in the medium-run by weighing on the amount of innovation and technology adoption (Stadler 1990; Comin and Gertler 2006; Anzoátegui et al. 2019; Bianchi, Kung and Morales 2019; Barlevy 2007).[2] Focusing mostly on R&D spending as their measure of innovation, these papers find evidence that innovation declines during downturns and that this can have medium-run effects on productivity and output. Different papers propose different mechanisms for the decline in innovation, including reduced incentives due to lower demand (Comin and Gertler 2006; Anzoátegui et al. 2019; Barlevy 2007) or tighter credit market conditions (Bianchi, Kung and Morales 2019; Queralto 2020). Some papers have also argued that innovation will increase during downturns, as weaker economic activity can free up resources and make innovation cheaper (Aghion et al. 2012).

Recent papers have begun to explore whether monetary policy can influence innovation and technology adoption and, through this, have medium-run effects on productivity and economic output. Jordà, Singh and Taylor (2020), using cross-country data, provide empirical evidence that contractionary monetary shocks lead to lower productivity growth over the medium-term. They build a New Keynesian model with endogenous TFP growth, to motivate their empirical findings.

Moran and Queralto (2018) provide more evidence on the mechanisms for the US. Using a Vector Auto Regressive (VAR) model, they find that contractionary monetary policy lowers innovative activity, as measured by R&D spending. In turn, lower R&D spending tends to lead to slower productivity growth and therefore lower economic output. They build these mechanisms into a New Keynesian model where weaker economic conditions, including those due to contractionary monetary policy, lower the returns to innovation and adoption leading to slower innovation and slower adoption of innovation. Monetary policy can thus influence productivity and economic output in the medium-term. Their model indicates that the medium-run effects of policy and conditions on productivity and output can be sizeable and thus of first order importance to policymakers. They estimate that US output and productivity would have been permanently 2 per cent higher had monetary policy not been constrained by the effective zero lower bound following the Global Financial Crisis. Similarly, US productivity and output would have been permanently 1 per cent higher if the tightening of monetary policy from 2016 had been more gradual.

2 In a related literature, Sedláček and Ignaszak (2021) consider the role that firm-level demand can play in incentivising innovation, and, in turn, in affecting aggregate growth.

Ma (2023) focuses on patenting as a measure of innovative activity, again for the US. He finds that the value and number of patents rises following an expansionary monetary policy shock, which in turn can contribute to higher productivity. He finds that firms with higher liquidity are more responsive than firms with lower liquidity, suggesting that financing constraints play an important role. In a heterogenous firm model, he shows how this financing constraint mechanism can contribute to longer-lived impacts of monetary policy shocks on productivity and output.

Ma and Zimmerman (2023) focus on similar measures to the two previously mentioned papers, such as R&D spending and patenting, as well as venture capital funding, and find similar results to the above papers for the US. Similar to our paper they explore the channels through which monetary policy can affect innovative activity. They find that R&D and patenting are more responsive to monetary policy shocks in cyclical industries, suggesting monetary policy affects innovation by influencing demand conditions – the demand channel. They also find evidence that venture capital funding falls following a contractionary monetary policy shock, which in turn is likely to limit the amount of funds available for innovative activity – the financial channel. Applying standard multipliers from innovative activity to output, they suggest that a 100 basis point contractionary shock could lead to output that is 1 per cent lower 5 years after the shock.

Amador (2022) focuses on cross-country measures of the take-up of general-purpose technologies, like electrification. He finds that contractionary policy leads to slower diffusion of these technologies, which can weigh on output in the medium-term.

Finally, our paper also touches on the large literature exploring global spillovers from US monetary policy. While this literature tends to focus on the effects of US policy on interest rates, investment or output in other countries (e.g., Georgiadis 2016; Kearns, Schrimpf and Xia 2022; Arbatli-Saxegaard et al. 2022), we extend this to consider firms' innovative activity.

3. Data and Methodology

3.1 Data

We focus on four different measures of innovative activity.

The first three are narrow measures of innovative activity that have been considered in the literature.

- The (log) flow of new patents filed in Australia by Australian residents from IP Australia's IPLORD database (IP Australia, 2023). This is a fairly narrow measure of innovative activity that is more likely to capture the creation of 'new-to-world' innovation and which has previously been linked to economic growth (Atun, Harvey and Wild 2007). [3]

- The (log) flow of new trademarks filed in Australia by Australian residents from IP Australia's IPLORD database. This is a slightly broader measure of innovation that will likely capture 'new-to-firm' innovation (Mendonça, Pereira and Godinho 2004; Claes 2005).

3 The claim that patents lead to radical innovation is contested, as patents can be seen as anti-competitive (Argente et al. 2020). Ma (2023) uses patents in his research on the US; for completeness, we test to see if monetary policy shocks impact patents in Australia.

- Aggregate (log) R&D spending from Australian Bureau of Statistics (ABS) National Accounts. R&D has been linked to both higher novelty of innovation and adoption of innovation (Majeed and Breunig 2022; D'Este, Amara and Olmos-Peñuela 2016). This is a slightly broader measure of innovative activity that will capture spending on the creation of 'new-to-world' innovation, as well as spending to adopt innovations.

All three variables are observed quarterly from March 1994 through December 2019.

Our fourth measure of innovative activity is a survey measure of innovation collected in the ABS Business Characteristics Survey (BCS). This is a broad measure of innovation based on the Oslo Manual (2018), the OECD benchmark for innovation measurement. It captures around 8,000 firms each year from 2005/06 to 2019/20. Each year firms are asked whether they introduced new or significantly improved: goods or services; operational processes; organisational/managerial processes; or marketing methods. This measure includes adoption of existing technologies or processes, which is an important mechanism in models such as that of Moran and Queralto (2018). It is also particularly important in Australia which tends to be an importer of innovation: only around 5 in 100 firms in the survey report introducing a new-to-world innovation, whereas 50 in 100 firms report some form of innovative activity.

The BCS is a census of firms with more than 300 employees and a stratified random sample for firms with less than 300 employees. Stratification by industry and business size is implemented to produce data that are representative of Australian businesses. The ABS do not provide sample weights so we use unweighted data. In our results across all firms, large firms will be somewhat overweighted.

Firms with fewer than 300 employees are included on a rotating 5-year basis. This could create some biases in our results, particularly if small and large firms respond differently to shocks as the share of large firms in our sample will be larger as we consider longer time horizons. Taking any given year as a base period, only 2/5th of small firms will still be in the sample in 4 years' time. Splitting the sample into small and large firms helps to limit any potential bias.[4]

Another potential bias could come from attrition. If monetary policy shocks caused firms to exit, and if the remaining firms were more likely to be innovative, it may appear that the share of firms innovating has increased, but this apparent result would merely be reflecting a positive survivorship bias. To avoid this issue, our main regressions focus on firms with at least 5 observations. These are firms who do not exit during their period in the sample. Our firm-level results thus measure the intensive margin effect of monetary policy on firm innovation only. That said, the results are very similar if we do not impose this restriction. We also directly tested whether monetary policy affects the probability of firm exit, and whether the effect differs by innovator status. We do not detect any difference between innovators and non-innovators in terms of exit post-shock.

We exclude micro-businesses from our study by removing all firms with one full time equivalent (FTE) employee or less. Excluding micro firms is standard practice in the literature.

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4 As a robustness test, we also estimated the models, including firms in the regression for horizons 0, 1 and 2, only if we could observe their innovation at horizon 3. This ensured that the share of large and small firms remains balanced. The results by firm size were similar to our baseline, though there was slightly more evidence of an immediate effect.

The BCS data are available at the firm level and are linked to the ABS Business Longitudinal Analysis Data Environment (BLADE), which contains demographic and tax data from administrative sources. This allows us to model innovation at the firm level accounting for firm-level covariates and to explore heterogenous effects across firm types. A table of descriptive statistics for the firm-level sample is included in Appendix Tables A1 and A2. We provide descriptive statistics for all firms and for firms split by firm size, by exporting status and by foreign ownership.

3.2 Methodology

We do not explicitly develop our own theoretical model for the analysis but the channels of monetary policy that we consider are those of the model developed in other papers such as Moran and Queralto (2018) and Ma (2023). Our econometric methodology is motivated by testing the implications of such models.

3.2.1 Monetary Policy Shocks

An inherent difficulty in examining the effect of monetary policy on innovation is that the official cash rate will be endogenous. That is, innovation activity and monetary policy are co-determined by other factors. For example, the RBA is likely to raise rates if it expects economic activity and inflation to increase. But improvements in economic activity might also spur further innovative activity. Thus, it might appear that higher interest rates lead to more innovation when both are moving with economic conditions.

To get around this endogeneity issue we use a monetary policy shock measure developed in Beckers (2020). This is a Romer and Romer (2004)-style approach, in that it measures shocks as divergences of the observed policy rate from what would be expected based on an estimated policy reaction function. This approach is widely used in the macro literature (Ramey 2016). For studies examining the impact of monetary policy on innovation, our shock variable is similar to Ma and Zimmerman (2023). Ma (2023) uses a monetary policy shock measure based on high-frequency changes in interest rates around announcements. We include a high frequency-based shock measure as part of our sensitivity analysis.

Specifically, Beckers (2020) estimates an augmented Taylor rule that includes a forecast for economic conditions and a number of indicators of financial conditions (e.g. bond spreads, option-implied volatility). The shocks are then constructed as the deviation of the actual policy rates from that implied by the rule. This approach removes the anticipatory component of monetary policy by purging changes in the policy rate of the central bank's systematic response to its own forecasts. We use the continuous measure that also orthogonalises the shock with respect to market expectations for the policy rate, though our results are near identical using the measure without this step.

We adopt this measure as our preferred shock measure (Figure A1) because previous research found that it is able to overcome the so-called price-puzzle in Australian data: that contractionary monetary policy is often estimated to raise prices. This is not the case for simpler Romer and Romer (2004) style shocks (Bishop and Tulip 2017) or measures based on high-frequency changes in bond yields over a 90-minute window around announcements (Hambur and Haque 2023). We nonetheless consider these other measures for robustness in Appendix Tables B1-B4.

3.2.2 Estimation

We employ a local projection regression (Jordà 2005) to trace out the effect of a monetary policy shock at time t on our measures of innovative activity over a number of different time horizons h. This is a common approach in the literature (Ma 2023; Jordà, Singh and Taylor 2020; Durante, Ferrando and Vermeulen 2022). Our regression takes the following form:

$$Inn_{i,t+h} = \beta_h shock_t + \alpha_h Inn_{i,t-1} + \sum_{j=1}^{1} x_{h,j} Controls_{t-j} + v_{i,t+h} \qquad (1)$$

Where $h \geq 0$, denotes the time horizon, t denotes time and i indexes the firm (for firm-level regressions). We also estimate equation (1) using aggregate variables which we can represent identically to the above, simply by dropping the i subscripts. $Inn_{i,t+h}$ is our measure of innovation. This is either at the aggregate level for (log) R&D, (log) patents or (log) trademarks, or at the firm level for our 0/1 indicator of whether a firm innovates. $shock_t$ is our continuous measure of monetary policy shocks described above. Typically, local projections control for macroeconomic variables to improve efficiency (Jordà , 2005). We control for standard aggregate measures: Gross Domestic Product (GDP), the Consumer Price Index (CPI) and the trade-weighted index (TWI) exchange rate. For our firm-level regressions we also control for: (log) employment, turnover growth, (log) capital expenditure and age (a dummy if a firm is more than four years old). We include these with one lag.[5]

For firm-level regressions we cluster the standard error at the period level, reflecting the fact that the key variable of interest varies across time but not across firms. As a result, we have a small number of clusters, which can bias our standard errors downwards. To address this, we assess significance based on a t-distribution with T-n degrees of freedom, where T is the sample length and n is the number of coefficients on variables that do not vary across firms, as discussed in Cameron and Miller (2015). We do not allow for serial correlation as this is captured in the control variables.

4. Results

4.1 Aggregate innovation measures

In this section, we examine how monetary policy shocks affect patents, trademarks and R&D activity. We focus on the coefficients of the shock variable in equation (1) over different time horizons and trace them out in Figure 1. For consistency, all the results of this paper are based on a 100 basis point contractionary shock.

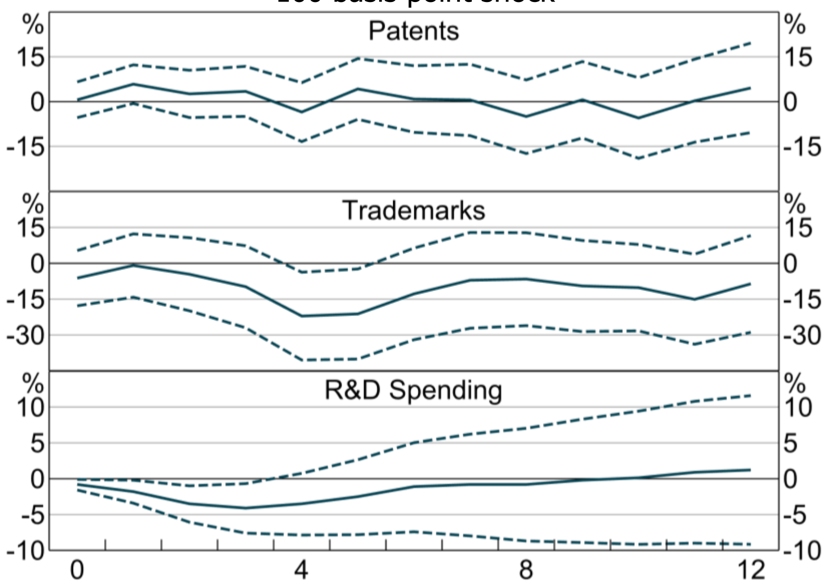
Unlike the US (Ma 2023), monetary policy shocks have no effect on the number of patents filed (Figure 1; top panel). This is consistent with Australia tending to be an importer of new technologies, rather than a producer (Majeed and Breunig 2022) and Australia having fewer patents filed compared to the US. However, when focusing on broader measures of innovation there is evidence that monetary policy can have a significant influence.

5 The results are robust to including more or fewer lags of the RHS variables, as well as to including contemporaneous controls, which removes the implicit assumption that monetary policy cannot affect current conditions (Ramey 2016). Exclusion of the control for age does not affect the results.

Figure 1 shows the effect of a contractionary monetary policy shock on three aggregate measures of innovation. In the year following a 100 basis point contractionary shock, R&D spending declines by almost 5 per cent (bottom panel), while the number of trademarks falls by over 15 per cent one-to-two years after the shock (middle panel). The response of R&D spending is somewhat larger than documented in Moran and Queralto (2018), though it is also shorter lived – they document a 0.8 per cent decline, with the peak effect around 4 years after the shock. In part, this appears to reflect our use of a local projection model instead of a Vector Auto Regression (VAR). When we estimate a simple 5-variable VAR where the shock is ordered first, as suggested by Plagborg-Møller and Wolf (2021), the peak effect is also around 5 per cent, but more sustained (see Appendix Figure B1).[6] Given that local projections (LP) may suffer from downward bias, see Herbst and Johannsen (2020), the fact that we find similar results using the VAR and the LP is reassuring.

Figure 1: Effect of Monetary Policy Shock on Aggregate Innovation Measures

100 basis point shock



Note: Results from local projection model of aggregate innovation metrics on monetary policy shock. Trademark sample excludes 1994-1995 due to break in time series. Patents and trademarks include only those with Australian filers. Dashed lines show 90 per cent confidence intervals, with Huber/White standard errors. Models have 8 lags of growth in GDP trade-weighted exchange rate index and CPI growth, and four lags of shocks and lagged dependent variable. Results robust to other specifications. Data are quarterly.

In either model, the peak effect we find is larger and occurs earlier compared to Moran and Queralto (2018).[7] Our results are in line with those from Ma and Zimmerman (2023), who also use LP and find that aggregate investment in intellectual property falls by around 1 per cent one to two years after the shock, and that listed company R&D spending falls by around 3 per cent, with a peak effect two to three years after the shock. More generally, the 5 per cent response, while large, is not unreasonable in the context of this series – over the sample, the year-ended growth rate of R&D

6 While the two should be equivalent if the VAR is correctly specified, truncation of the lags appears to be contributing to the longer-lived response in the VAR compared to the LP. This can be seen in comparing the VAR with two lags to the VAR with four lags.

7 We experimented with a VAR identified using timing restrictions as in Moran and Queralto (2018). This provided no evidence of a significant effect on R&D spending, likely reflecting the strong (and probably inaccurate) identification assumption.

spending has ranged between around negative 8 per cent and 22 per cent, with a standard deviation of around 7.5 per cent.[8]

4.2 Firm-level innovation and adoption measures

As discussed above, much of the literature to date has focused on relatively narrow measures of innovation that are unlikely to fully capture the broader effects of monetary policy on adoption of existing technologies by firms. This is the case even though technology adoption is a crucial mechanism in models such as that of Moran and Queralto (2018).

Focusing on our broader survey measure of innovation we find that a contractionary 100 basis point monetary policy shock has relatively little effect on the overall share of firms innovating (Table 1, top panel). But this average result hides very different outcomes for small and large firms. The share of small and medium enterprises (SMEs; less than 200 employees) innovating falls by 6 percentage points the year after a 100 basis point contractionary monetary policy shock (Table 1, middle panel). This equates to around 52,000 fewer firms innovating.

Table 1: Effect of 100 basis point shock on share of firms innovating
By firm size

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	-0.76	-2.76*	1.29	7.06**
(s.e.)	(1.65)	(1.47)	(2.09)	(2.67)
R^2	*0.20*	*0.14*	*0.11*	*0.09*
Observations	*45,053*	*35,635*	*26,302*	*17,536*
SMEs				
Effect	-2.85	-6.13***	-2.45	1.39
(s.e.)	(1.61)	(0.99)	(1.83)	(1.54)
R^2	*0.19*	*0.14*	*0.12*	*0.10*
Observations	*29,551*	*22,185*	*14,616*	*7,291*
Large firms				
Effect	3.47	2.70	5.02*	9.80*
(s.e.)	(2.64)	(2.65)	(2.35)	(4.46)
R^2	*0.19*	*0.11*	*0.07*	*0.06*
Observations	*15,502*	*13,450*	*11,686*	*10,245*
Difference by size significant at	5 per cent level	1 per cent level	1 per cent level	10 per cent level

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggested by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.
Source: Authors' calculations

In contrast, the share of larger firms (more than 200 employees) innovating increases by 5 percentage points two years after the shock, equating to around 200 firms (Table 1, last panel).

8 Note that the unconditional standard deviation is much larger than the standard deviation of the structural R&D shock from the small VAR discussed later, suggesting much of the volatility reflects other factors such as aggregate demand.

This latter finding may seem surprising in the context of the existing literature, but it is consistent with some of the broader innovation literature that argues that innovation may be countercyclical as firms may have an incentive to undertake longer run investments in innovation when input costs are relatively cheap and when demand is weak (Aghion et al. 2012). Larger firms may be better placed to take advantage of countercyclical conditions.

To put these numbers into context, from 2005/06 to 2019/20 the share of firms innovating rose consistently, increasing by around 7 percentage points by the end of the sample (Department of Industry, Science, Energy and Resources 2021). Given this, monetary policy appears to have meaningful effects on the share of firms innovating.[9] Moreover, the heterogeneity of results for different firms suggests that firms may be differentially exposed to different monetary policy channels. We explore this in section 5.

4.3 Robustness

In this section, we test to see if our results differ substantially when we use other monetary policy shock measures. We consider four measures:

- The change in the policy rate (cash rate) itself.
- A version of the Beckers (2020) shock that does not purge market expectations, which we call 'Beckers'.
- A Romer and Romer-style shock where the policy reaction function includes only economic variables and excludes the financial market variables used in Beckers (2020). This is taken from Bishop and Tulip (2017). We refer to this as 'BT'.
- A measure based on high-frequency changes in bond yields based on a 90-minute window around announcements (Hambur and Haque 2023), which we call 'levels shock'.

The results are provided in Appendix Tables B1-B4. Using the Beckers variable gives qualitatively and quantitatively similar results to those we discuss above, consistent with the high correlation between the two shock measures. The results with the BT variable and the change in the policy rate are also qualitatively similar, with SMEs decreasing their innovation and large firms increasing, though the effects are not statistically significant. Interestingly, the evidence for the levels shock is qualitatively different, with some evidence of a decline in innovation for large firms. However, given the shortcomings with this measure discussed in Hambur and Haque (2023), the results from the Romer and Romer style shocks remain our preferred estimates.

5. Through which channels does monetary policy affect innovation?

As discussed in the literature review, there are several channels through which monetary policy and economic conditions could lower the amount of innovative activity in the economy. One is the

9 The response may seem large relative to how much the share of innovating firms in the economy varies. But it is important to keep in mind that a 100 basis point monetary policy shock is larger than any shock which has occurred in the sample. The downward bias in local projections documented by Herbst and Johannsen (2020) would be working against our ability to find significant results, but should not be influencing our comparisons across different firm types.

demand channel: contractionary monetary policy may weaken aggregate demand and therefore lower the returns to innovation. Another is the credit constraint channel: monetary policy may lead to tighter credit conditions and make cash-flow constraints more binding for some firms. In turn this may lessen their ability to fund and undertake innovative activity. To consider the importance of these channels we compare outcomes for firms that we would expect to be more exposed to the channels to outcomes for firms that we would expect to be less exposed.

5.1 Demand channel

Aggregate demand in the economy is an important channel for monetary policy. As a contractionary monetary policy shock lowers aggregate demand in the economy, it also lowers the potential future profits of a firm. As the likelihood of future profits is the key reason for firms to innovate (Aghion and Howitt 2008), the probability of firms innovating can decrease as aggregate demand falls.

To consider the importance of the demand channel, we examine outcomes for exporting and non-exporting firms. Exporting firms are likely to be less exposed to domestic conditions, as their sales are not determined exclusively by the domestic economy. To do this we interact our shock variable with a dummy variable that takes value one if a firm ever exported while in the sample and zero otherwise. We use this to trace out the effect of a shock separately for exporters and non-exporters.

Consistent with the demand channel playing an important role, the negative effect of contractionary monetary policy on innovation is less evident for exporters (Table 2). These results are similar for large firms and SMEs (Appendix Tables B5 and B6), though there is only a statistically significant difference between exporters and non-exporters for the large firms. This suggests that the results do not simply reflect the fact that exporters tend to be larger, though that may account for part of the difference between exporters and non-exporters.

Table 2: Effect of 100 basis point shock on share of firms innovating

By exporter status

	Year 0	Year 1	Year 2	Year 3
Exporter				
Effect	0.24	1.60	4.29	8.83*
(s.e.)	(2.12)	(1.96)	(2.49)	(4.01)
R^2	*0.19*	*0.12*	*0.09*	*0.06*
Observations	*17,974*	*14,734*	*11,672*	*8,904*
Not exporter				
Effect	-1.19	-5.58***	-1.14	4.59**
(s.e.)	(1.78)	(1.43)	(1.92)	(1.93)
R^2	*0.19*	*0.12*	*0.10*	*0.10*
Observations	*27,079*	*20,901*	*14,630*	*8,632*
Difference by export status significant at:	N/A	1 per cent level	1 per cent level	N/A

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

It is important to note that there could be other differences between exporting and non-exporting firms that affect these results. For example, exporting firms tend to be more productive and may have better management. To try to isolate the demand effects, we next re-estimate the regression, instead using a measure of US monetary policy shocks taken from Choi, Willems and Yoo (2023).[10] If the previous results reflected the demand channel, rather than other inherent differences between exporters and non-exporters, we might expect exporters to respond more strongly to overseas monetary policy shocks as they are more directly exposed to foreign demand than are non-exporting firms. This is the 'trade channel' of policy spill overs (Arbatli-Saxegaard et al. 2022). This exercise is also valuable as it provides (to our knowledge) the first evidence on spillovers from US monetary policy onto innovation in another country.

The first thing to note is that contractionary US monetary policy shocks do appear to lower the share of firms innovating in Australia (Table 3). The effects appear larger, compared to the domestic shock. However, it is difficult to compare the magnitudes given the two shocks are identified using two different techniques in separate country contexts and thus have different implied persistence and may be picking up different types of policy responses.

Table 3: Effect of 100 basis point US shock on share of firms innovating

By export status

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	-5.73	-11.02***	-8.16	-7.59
(s.e.)	(5.40)	(3.20)	(5.17)	(8.88)
R^2	*0.20*	*0.14*	*0.11*	*0.09*
Observations	*45,053*	*35,635*	*26,302*	*17,536*
Exporters				
Effect	-7.38	-10.86*	-9.76	-11.28
(s.e.)	(6.97)	(5.37)	(6.29)	(10.17)
R^2	*0.19*	*0.12*	*0.09*	*0.06*
Observations	*17,974*	*14,734*	*11,672*	*8,904*
Non-exporters				
Effect	-4.53	-10.61**	-6.71	4.59
(s.e.)	(5.04)	(3.79)	(4.95)	(5.89)
R^2	*0.19*	*0.12*	*0.10*	*0.09*
Observations	*27,079*	*20,901*	*14,630*	*8,632*
Difference by exporter status significant at	N/A	N/A	N/A	N/A

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

10 This measure is based on high-frequency changes in bond yields. We used this measure given the availability of a wide range of country shock variables, which could facilitate future analysis.

The second key finding is that the response for exporters appears larger than for non-exporters, which is the opposite of the findings when we considered a shock to Australian monetary policy. This is observed for both SMEs and large firms (Appendix Tables B7 and B8) and is consistent with other work focusing on the response of firm-level investment and sales in foreign countries following US policy shocks (Arbatli-Saxegaard et al. 2022). While the differences are not statistically significant, the greater sensitivity of exporters to foreign shocks, and of non-exporters to domestic shocks, provides further evidence of the importance of the demand channel.

5.2 The credit constraint channel

The credit constraint channel of monetary policy captures any way in which contractionary monetary policy (or weaker economic conditions) makes it harder for a firm to finance innovative activity; see Chapter 14 of Bernanke (2022), for example. This can reflect: tighter aggregate credit supply; lower asset prices which reduce borrowers' collateral value and therefore borrowing capacity; the 'financial accelerator channel' (Bernanke, Gertler and Gilchrist 1999); or lower liquidity due to lower revenue or higher interest payments making existing financing constraints more binding (Jeenas 2019).

To examine the credit constraint channel directly, we explore an additional question in the BCS. This question asks whether a lack of access to additional funds is hampering the business's ability to innovate. We examine whether monetary policy shocks lead to a change in the share of firms reporting that access to additional funds is limiting their innovative activity.[11]

Consistent with the credit constraint channel being important, contractionary monetary policy shocks lead to an increase in the likelihood that firms report that lack of funds is significantly hampering their ability to undertake innovation (Table 4). This is almost entirely driven by SMEs, which is consistent with the evidence that SMEs have a larger decline in innovation following a monetary policy shock. To put the results in context, over the sample, around 17 per cent of SMEs note that a lack of funds is hampering their innovation (compared to 8 per cent for large firms). So, a 100 basis point shock (which is very large historically) would cause the share of SMEs reporting that a lack of funds are hampering innovation to increase by around 15-20 per cent. These findings are also consistent with the broader literature that finds that SMEs are more likely to be credit or cash constrained than larger firms — for example Mancusi and Vezzulli (2010) and Bakhtiari et al. (2020).

11 The survey question asks firms about what factors are hampering their innovative activity. As well as a lack of access to additional funds, the factors are: lack of skilled workers; cost of development; regulations and compliance; uncertain demand for new goods/services. Firms can select more than one factor.

Table 4: Effect of 100 basis point shock on share of firms reporting lack of funds hampering innovation

By firm size

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	1.40**	2.06***	1.44	2.37***
(s.e.)	(0.63)	(0.63)	(0.99)	()
R^2	*0.28*	*0.32*	*0.35*	*0.39*
Observations	*42,138*	*32,901*	*23,826*	*15,245*
SMEs				
Effect	2.02*	2.92***	2.45*	3.67***
(s.e.)	(1.00)	(0.70)	(1.30)	(0.65)
R^2	*0.28*	*0.32*	*0.34*	*0.37*
Observations	*28216*	*20,966*	*13,518*	*6,360*
Large firms				
Effect	0.16	0.63	0.25	1.10
(s.e.)	(0.49)	(1.41)	(1.19)	(0.83)
R^2	*0.28*	*0.34*	*0.39*	*0.42*
Observations	*13,922*	*11,935*	*10,308*	*8,885*
Difference by size significant at	N/A	N/A	10 per cent level	10 per cent level

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.
Source: Authors' calculations

This provides fairly strong evidence that the credit constraint channel is important. As a further test, but one which relies less heavily on self-reported data, we examine whether the results differ for foreign- and domestically-owned firms. Foreign-owned firms may be better able to access credit from overseas markets or from their overseas parent (Dahlquist and Robertsson 2001). Thus, they may be more sensitive to the global, not domestic, cost of capital and hence less affected by domestic credit conditions.[12]

To look at whether foreign ownership mitigates the effect of monetary policy on innovation, we interact the monetary policy shock variable with a dummy variable for foreign ownership and then trace out the effects for domestically- and foreign-owned firms. If a firm indicated it has any level of foreign ownership, it is categorised as foreign-owned. For this analysis we focus on large firms only, given the number of foreign-owned SMEs is small.

There is some evidence that contractionary monetary policy has less of a negative effect on foreign-owned firm innovation, compared to domestically-owned firms (Table 5). While this evidence is less direct and could reflect factors other than the ability to access overseas financing, it is consistent

12 That said, the global cost of capital may affect domestic costs.

with the credit supply channel playing an important role in the transmission of monetary policy to innovative activity and reinforces the above, more direct results.

Table 5: Effect of 100 basis point shock on share of firms innovating
By foreign ownership status, large firms

	Year 0	Year 1	Year 2	Year 3
Foreign owned				
Effect	6.78**	6.89**	7.58**	9.52*
(s.e.)	(2.96)	(3.09)	(3.34)	(4.80)
R^2	*0.20*	*0.11*	*0.08*	*0.07*
Observations	*9,556*	*8,402*	*7,382*	*6,528*
Not foreign owned				
Effect	-1.73	-4.10	0.81	9.99
(s.e.)	(2.22)	(3.18)	(3.02)	(5.79)
R^2	*0.19*	*0.10*	*0.07*	*0.05*
Observations	*5,946*	*5,048*	*4,304*	*3,717*
Difference by size significant at	1 per cent level	10 per cent level	1 per cent level	N/A

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.
Source: Authors' calculations

6. Macroeconomic effects on productivity

Thus far we have focused on measures of innovation rather than productivity. Moran and Queralto (2018) demonstrate in their model and empirically that shocks to R&D spending have an effect on productivity in the medium-run. They show this focusing on the US and using a cross-country panel (that includes Australia). However, given the vastly different structures of the Australian and US economies, it is worth examining whether the results for the US hold when focusing only on Australia.

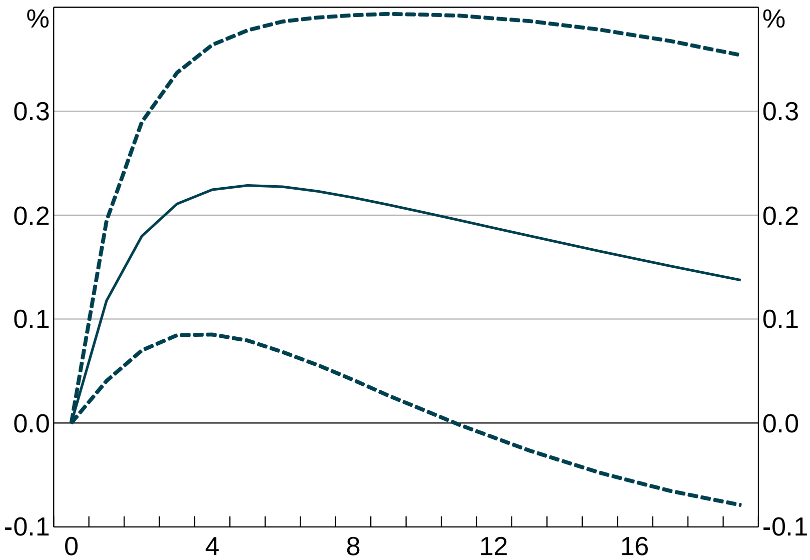
To examine if their results hold for Australia, we reproduce the small VAR model used in Moran and Queralto (2018). We estimate a small, three variable VAR with annual data on GDP, total-factor productivity from Bergeaud, Cette and Lecat (2016), and R&D spending from 1988 to 2019. As in Moran and Queralto (2018) we examine the effect of R&D shocks, which are identified by ordering R&D last in a Cholesky decomposition. This implies that R&D cannot affect TFP contemporaneously, consistent with the fact that it generally takes time for R&D expenditure to result in new technologies. While the assumption used to identify may be strong, it is the same as used in Moran and Queralto (2018) and it should highlight whether similar economic patterns and mechanisms are evident in the US and Australia.

Taking this approach, we find that an R&D shock leads to a persistent increase in TFP that peaks around 5 years after the shock (Figure 2). The magnitudes of the responses are somewhat larger than Moran and Queralto (2018) report, with an equivalent size increase in R&D (4 per cent) leading to a 1.6 per cent increase in TFP, compared to 0.4 per cent increase in Moran and Queralto (2018). In the data, the volatility of the R&D shock is an order of magnitude smaller (around ½ per cent, compared to 4 per cent in Moran and Queralto (2018)), suggesting that such a large shock would be extremely unusual.[13] Again, our results are somewhat more in line with Ma and Zimmerman (2023). Drawing on other estimates, they suggest that a 100 basis point shock would lower TFP and output by 0.5 to 1 per cent, whereas our estimates put this at around 1.6 per cent.

Interestingly, the response is also less long-lived compared to Moran and Queralto (2018): the peak occurs around 5 years after the shock for Australia, compared with around 8 years in the US. This could potentially reflect the fact that Australia imports innovation. While adoption of technologies declines, the actual stock of global knowledge is unaffected, allowing firms to catch up more quickly (though still with a substantial lag).

Overall, while the exact magnitudes differ somewhat to Moran and Queralto (2018), these results suggest that similar mechanisms by which decreasing innovation and R&D could have longer-lasting effects on productivity are evident in Australia.

Figure 2: Effect of an R&D Shock on Total Factor Productivity
Aggregate data, one standard deviation shock



Note: Figure shows response of TFP to an R&D spending shock from a VAR containing the log levels of real GDP, real R&D spending, and TFP. Response based on Cholesky decomposition with R&D spending ordered last. VAR(1) model. Dashed lines are the 90 per cent confidence interval. Data are annual.

7. Conclusion

There is a small but growing literature arguing that macroeconomic conditions and monetary policy shocks can have medium-run effects on productivity and therefore living standards and long-run economic activity. This has important implications for macroeconomic policy. While such effects are likely to cancel out over a cycle, the potential for medium-run productivity scarring increases the importance of macro-stabilisation policy. It also increases the costs associated with such policies being constrained, such as at the effective zero lower bound on interest rates. And it potentially

13 We experimented with looking directly at the effects of monetary policy shocks on productivity. We were unable to identify any effects. However, this likely reflects the lack of quarterly data on total-factor productivity, resulting in our estimates being based on a small number of annual observations and highly aggregated shocks.

alters the trade-offs a central bank faces when stabilising inflation and activity in the face of supply shocks, provided that inflation expectations can be kept anchored.

We provide the first evidence on the potential medium-run effects of monetary policy shocks and (indirectly) of economic conditions for a small open economy that imports innovation rather than creating it. Consistent with the overseas literature, we find evidence for Australia that contractionary monetary policy shocks are associated with a decline in R&D spending. We also find that declines in R&D spending are associated with lower levels of productivity in the medium-term.

When focusing on broader measures of innovation that may better capture adoption, we find substantial heterogeneity in the response of firms. SMEs are less likely to innovate and adopt after a contractionary monetary policy shock, but large firms are more likely to do so. This appears to reflect the fact that SMEs and large firms are differentially exposed to the channels through which monetary policy can affect innovative activity. For example, exporting firms (which tend to be larger) are less likely to lower their innovative activity following a contractionary monetary policy shock seemingly because they are less exposed to the ensuing softening in domestic demand. Monetary policy appears to affect innovation by affecting demand in the economy – the demand channel of monetary policy. Contractionary monetary policy shocks also lead to an increase in the share of firms (particularly SMEs) reporting that financial constraints are preventing them from innovation. Monetary policy also appears to affect innovation by influencing financial conditions and constraints – the financial constraint channel of monetary policy.

A further novel aspect of our paper is considering the effects of US monetary policy shocks on the innovative activity of Australian firms. We find important spill overs from US monetary policy shocks onto the innovation activity of Australian firms. This effect is larger for Australian firms who export, again consistent with the importance of the demand channel of monetary policy.

Our results confirm that monetary policy, both domestic and foreign, and economic conditions can have medium-run effects on productivity and output by influencing the amount of innovative activity that occurs. However, they do not speak to the longer-run structural decline in productivity growth observed over the past two decades. Previous work has shown that this reflects structural declines in labour mobility, technology adoption and competition which appear unrelated to the economic cycle (e.g., Andrews and Hansell 2021 Andrews et al. 2022; Hambur 2023).

References

Aghion, Philippe, and Peter W. Howitt. 2008. *The Economics of Growth.* The MIT press.

Aghion, Philippe, Nicolas Bermna, Laurent Eymard, Philippe Askenazy, and Gilbert Cette. 2012. "Credit constraints and the cyclatlity of R&D invesment: Evidence from France." *Journal of the European Economic Association*, 10(5): 1001-1024. https://doi.org/10.1111/j.1542-4774.2012.01093.x.

Amador, Sebastián. 2022. *Hyteresis, Endogenous Growth, and Monetary Policy*. Working Paper No. 348, University of California David Department of Economics. http://hdl.handle.net/10419/267012.

Andrews, Dan, Nathan Deutscher, Jonathan Hambur, and David Hansell. 2020. *The Career Effects of Labour Market Conditions at Entry*. Working Paper No. 2020-01, Australian Government: The Treasury. https://treasury.gov.au/sites/default/files/2020-06/p2020-85098-202006.pdf.

Andrews, Dan, Jonathan Hambur, David Hansel and Angus Wheeler. 2022, *Reaching for the Stars: Australian Firms and the Global Productivity Frontier*, Working Paper No. 2022-01, Australian Government: The Treasury. https://treasury.gov.au/sites/default/files/2022-02/p2022-243535.pdf

Andrews, Dan and David Hansell. 2021. "Productivity-Enhancing Labour Reallocation in Australia." *The Economic Record*, 97(317): 157-169. http://DOI: 10.1111/1475-4932.12601.

Anzoátegui D., D. Comin, M. Gertler and J. Martinez. 2019. "Endogenous Technology Adoption and R&D as Sources of Business Cycle Persistence." *American Economic Journal: Macroeconomics*, 11(3): 67-110.

Arbatli-Saxegaard Elif C., Melih First, Davide Furceri, and Jeanne Verrier. 2022. *U.S. Monetary Policy Shock Spillovers: Evidence from Firm-level Data*. Working Paper 22/191, International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2022/09/16/U-S-523572.

Argente, David, Salome Baslandze, Douglas Hanley, and Sara Moreira. 2020. *Patents to Products: Innovation, Product Creation, and Firm*. Working Paper No. 2020-4, Federal Reserve Bank of Atlanta. https://doi.org/10.29338/wp2020-04.

Atun, Rifat, Ian Harvey, and Joff Wild. 2007. "INNOVATION, PATENTS AND ECONOMIC GROWTH." *International Journal of Innovation Management,* 11(2). https://doi.org/10.1142/S1363919607001758.

Bakhtiari, Sasan, Robert Breunig, Lisa Magnani, and Jacquelyn Zhang. 2020. "Financial Constraints and Small and Medium Enterprises: A Review." *Economic Record*, 96(315): 506–523. https://docs.iza.org/dp12936.pdf.

Ball, Laurence M. 2009. *Hysteresis in Unemployment: Old and New Evidence*. Working Paper No. 14818, National Bureau of Economic Research. https://doi.org/10.3386/w14818.

Baqaee, David, Emmanuel Farhi, and Kunal Sangani. Forthvoming. "The Supply-side Effects of Monetary Policy", *Journal of Political Economy*. https://doi.org/10.1086/727287

Barlevy, Gadi. 2004. "The Cost of Business Cycles Under Endogenous Growth." *American Economic Review*, 94(4): 964-990. https://doi.org/10.1257/000282042002615.

Barlevy, Gadi. 2007. "On the Cyclicality of Research and Development." *American Economic Review*, 97(4): 1131-1164. https://doi.org/10.1257/aer.97.4.1131.

Beckers, Benjamin. 2020. *Credit Spreads, Monetary Policy and the Price Puzzle*. Research Discussion Paper RDP 2020-01, Reserve Bank of Australia. https://www.rba.gov.au/publications/rdp/2020/pdf/rdp2020-01.pdf.

Benigno, Gianluca, and Luca Fornaro. 2018. "Stagnation Traps." *The Review of Economic Strudies*, 85(3): 1425-1470. https://doi.org/10.1093/restud/rdx063.

Bergeaud, Antonin, Gilbert Cette, and Rémy Lecat. 2016. "Productivity Trends in Advanced Countries between 1890 and 2012." *Review of Income and Wealth*, 62(3): 420–444. https://doi.org/10.1111/roiw.12185.

Bernanke, Ben S. 2022. *21st Century Monetary Policy: The Federal Reserve from the Great Inflation to COVID-19.* Manhatten: WW Norton & Company.

Bernanke, Ben S., Mark Gertler and Gilchrist. 1999. "The financial accelerator in a quantitative business cycle framework." in: J. B. Taylor and M. Woodford (ed.), Handbook of Macroeconomics, edition 1, volume 1, chapter 21, pages 1341-1393, Elsevier.

Bianchi, Francesco, Howard Kung, and Gonzalo Morales. 2019. "Growth, slowdowns, and recoveries." *Journal of Monetary Economics*, 101: 47-63. https://doi.org/10.1016/j.moneco.2018.07.001.

Bishop, James, and Peter Tulip. 2017. *Anticipatory Monetary Policy and the' Price Puzzle'*. Research Discussion Paper RDP 2017-02, Reserve Bank of Australia. https://www.rba.gov.au/publications/rdp/2017/pdf/rdp2017-02.pdf.

Blanchard, Olivier J., and Lawrence H. Summers. 1986. "Hysteresis and the European Unemployment Problem." *NBER Macroeconomics Annual*, 1(1986): 15-78. https://doi.org/10.2307/3585159.

Brown, James R., Steven M. Fazzari, and Bruce C. Petersen. 2009. "Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom." *The Journal of Financie*, 64(1): 151-185. https://doi.org/10.1111/j.1540-6261.2008.01431.x.

Cameron, A. Colin, and Douglas L. Miller. 2015. "A Practitioner's Guide to Cluster-Robust Inference." *The Journal of Human Resources*, 50(2): 317-372. https://doi.org/10/3368/jhr.50.2.317.

Choi, Sangyup, Tim Willems, and Seung Yong Yoo. 2023. *Revisiting the Monetary Transmission Mechanism Through an Industry-Level Differential Approach*. Working Paper No. 2022/017, International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2022/01/28/Revisiting-the-Monetary-Transmission-Mechanism-Through-an-Industry-Level-Differential-512222.

Claes, M. (2005). *Trademarks Statistics as Innovation Indicator? – A Micro Study*. Working Paper No. 2005/17, Lund University. https://portal.research.lu.se/en/publications/trademark-statistics-as-innovation-indicators-a-micro-study.

Comin, Diego, and Mark Gertler. 2006. "Medium-term Business Cycles." *American Economic Review*, 96(3): 523-551. https://www.jstor.org/stable/30034060.

Dahlquist, Magnus, and Göran Robertsson. 2001. "Direct foreign ownership, institutional investors, and firm characteristics." *Journal of financial economics,* 59(3): 413-440. https://doi.org/10.1016/S0304-405X(00)00092-1.

Davis, Steven J., and John C. Haltiwanger. 2021. *Dynamism diminished: The role of housing markets and credit conditions*. Working Paper No. 25466, National Bureau of Economic Research. https://doi.org/10.3386/w25466.

Department of Industry, Science, Energy and Resources. 2016. *Australian Innovation System Report 2016*. Canberra, Australia: Office of the Chief Economist, Department of Industry, Science, Energy and Resources. https://www.industry.gov.au/data-and-publications/australian-innovation-system-report/australian-innovation-system-report-2016.

Department of Industry, Science, Energy and Resources. 2021. *Australian Energy Update 2021: September 2021*. Canberra: Australian Energy Statistics. https://www.energy.gov.au/publications/australian-energy-update-2021.

D'Este, Pablo, Nabil Amara, and Julia Olmos-Peñuela. 2016. "Fostering Novelty While Reducing Failure: Balancing the Twin." *Technological Forecasting and Social Change,* 113: 280–292. https://doi.org/10.1016/j.techfore.2015.08.011.

Durante, Elena, Annalisa Ferrando, and Philip Vermeulen. 2022. "Monetary policy, investment and firm heterogeneity." *European Economic Review,* 148(104251). https://doi.org/10.1016/j.eurocorev.2022.104251.

Fornaro, Luca, and Martin Wolf. 2023. "The Scars of Supply Shocks: Implications for Monetary Policy." *Journal of Monetary Econmics*, 140: S18-S36. https://doi.org/10.1016/j.jmoneco.2023.04.003.

Garga, Vaishali, and Sanjay R. Singh. 2021. "Output Hystersis and Optimal Monetary Policy." *Journal of Monetary Economics*, 117: 871-886. https://doi.org/10.1016/j.jmoneco.2020.06.005.

Georgiadis, Georgios. 2016. "Determinants of global spilloers from US monetary policy." *Journal of Internal Money and Finance*, 67: 41-61. https://doi.org/10.1016/j.jimonfin.2015.06.010.

Hambur, Jonathan. 2023. "Product Market Comptition and its Implication for the Australian Economy." *Economic Record*, 99(234): 32-57. https://doi.org/10.1111/1475-4932.12707.

Hambur, Jonathan, and Qazi Haque. 2023. *Can We Use High-Frequency Yield Data to Better Understand the Effects of Monetary Policy and Its Communication? Yes and No!* Research Discussion Paper No. 2023-04, Reserve Bank of Australia. https://www.rba.gov.au/publications/rdp/2023/pdf/rdp2023-04.pdf.

Herbst, Edward P., and Benjamin K. Johannsen. 2020. *Bias in Local Projections*. Finance and Economics Discussion Series 2010-010R1, FEDS. https://edherbst.net/research/pdfs/hj_lp-revised.pdf.

Huber, Kilian. 2018. "Disentangling the Effects of a Banking Crisis: Evidence from German Firm and Countries." *American Economic Review*, 103(3): 868-898. https://doi.org/10.1257/aer.20161534.

Ikeda, Daisuke, and Takushi Kurozumi. 2019. "Slow Post-financial Crisis Recovery and Monetary Policy." *American Economic Journal: Macroeconomics,* 11(4): 82-112. https://doi.org/10.1257/mac.20160048.

IP Australia. "Intellectual Property Longitudinal Research Data (IPLORD)." Last modified August 30, 2023. Accessed December 19, 2023. https://aut.ac.nz.libguides.com/c.php?g=685064&p=4840642.

Jeenas, Priit. 2019. *Firm Balance Sheet Liquidity, Monetary Policy Shocks, and Investment Dynamics*. Working Paper No. 5, Department of Economics and Business, Universitat Pompeu Fabra and Barcelona GSE. https://crei.cat/wp-content/uploads/2020/06/Jeenas_JMP.pdf.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review,* 95(1): 161-82. https://doi.org/10.1257/0002828053828518.

Jordà, Òscar, Singh, Sanjay R., and Alan M. Taylor. 2020. *The Long-Run Effects of Monetary Policy*. Working Paper 2020-01, National Bureau of Economic Research. https://www.frbsf.org/economic-research/wp-content/uploads/sites/4/wp2020-01.pdf.

Kearns, Jonathan, Andreas Schrimpf, and Fan Dora Xia. 2022. "Explaining Monetary Policy Spillovers: The Matrix Reloaded." Research Discussion Paper RDP 2019-03, Reserve Bank of Australia. https://www.rba.gov.au/publications/rdp/2019/pdf/rdp2019-03.pdf.

Ma, Changseok. 2023. "Firm liquidity and the innovation channel of monetary policy." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4555571.

Ma, Yueran, and Kaspar Zimmermann. 2023. *Monetary Policy and Innovation*. Working Paper No. 31698, National Bureau of Economic Research. https://doi.org/10.3386/w31698.

Majeed, Omer, and Robert Breunig. 2022. "Determinants of innovation novelty: evidence from Australian administrative data." *Economics of Innovation and New Technology*, 32(8) 1249-1273. https://doi.org/10.1080/10438599.2022.2132239.

Majeed, Omer, Antonio Balaguer, David Hansell, Luke Hendrickson, Abasi Latcham, and Tessa Satherley. 2021. "What Drives High Growth? Characteristics of Australian Firms." *Economic Record,* 97(318: 350-364. https://doi.org/10.1111/1475-4932.12612.

Mancusi, Maria Luisa, and Andrea Vezzulli. 2010. *R&D, Innovation and Liquidity Constraints*. Working Paper No. 030, KITeS. https://ideas.repec.org/p/cri/cespri/kites30_wp.html.

Mendonça, Sandro, Tiago S. Pereira, and Manuel M. Godinho. 2004. "Trademarks as an indicator of innovation and industrial change." *Research Policy,* 33(9): 1385-1404. https://doi.org/10.1016/j.respol.2004.09.005.

Moran, Patrick, and Albert Queralto. 2018. "Innovation, productivity, and monetary policy." *Journal of Monetary Economics*, 93: 24-41. https://doi.org/10.1016/j.jmoneco.2017.10.006.

OECD. 2015. *The Future of Productivity*. OECD Publishing. OECD-2015-The-future-of-productivity-book.pdf

OECD. 2018. Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data. Fourth Edition. Paris: OECD Publishing. In series *The Measurement of Scientific, Technological and Innovation Activities*. https://www.oecd.org/science/oslo-manual-2018-9789264304604-en.htm.

Ouyang, Min. 2009. "The Scarring Effect of Recessions." *Journal of Monetary Economics*, 56(2): 184-199. https://www.economics.uci.edu/files/docs/workingpapers/2005-06/Ouyang-09.pdf.

Ouyang, Min. 2011. On the Cyclicality of R&D. *The Review of Economics and Statistics*, 93(2): 542–553. https://www.jstor.org/stable/23015953.

Plagborg-Møller, Mikkel, and Christian K. Wolf. 2021. "Local Projections and VARs Estimate the Same Impulse Responses." *Econometrica Journal of the Econometric Society* 89(2): 955-980. https://doi-org.virtual.anu.edu.au/10.3982/ECTA17813.

Queralto, Albert. 2020. "A model of slow recoveries from financial crises." *Journal of Monetary Economics,* 114: 1-25. https://doi.org/10.1016/j.jmoneco.2019.03.008.

Queralto, Albert. 2022. *Monetary Policy in a Model of Growth*. International Finance Discussion Papers No. 1340, Washington: Borad of Governors of the Federal Reserve System. https://www.federalreserve.gov/econres/ifdp/monetary-policy-in-a-model-of-growth.htm.

Ramey, V. A. 2016. "Chapter 2 - Macroeconomic Shocks and Their Propagation." *Handbook of Macroeconomics,* 2A: 71-162. https://dx.doi.org/10.1016/bs.hesmac.2016.03.003.

Romer, Christina D., and David H. Romer. 2004. "A New Measure of Monetary Shocks: Derivation and Implications." *The American Economic Review,* 94(4): 1055–1084. https://doi.org/10.1257/0002828042002651.

Sedláček, Petr, and Vincent Sterk. 2017. "The Growth Potential of Startups over the Business Cycle." *American Economic Review*, 107(10): 3182-3210. https://doi.org/10.1257/aer.20141280.

Sedláček, Petr, and Marek Ignaszak. 2021. *Productivity, Profitability and Growth*. Discussion Paper No. 16205, CEPR. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3886647.

Stadler, George W. 1990. "Business Cycle Models with Endogenous Technology." *The American Economic Review*, 80(4): 763-778. https://www.jstor.org/stable/2006706.

Webster, Elizabeth, and Paul Jensen. 2009. "Macroeconomic Conditions and Successful Commercialization." *Cambridge Journal of Economics,* 35(1): 123-44. https://www.researchgate.net/publication/46452456_Macroeconomic_Conditions_and_Successful_Commercialization.

Appendix A: Data Description

Our survey measure of innovation is based on the definition of innovation:

An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process).

This measure has been used in studies in Australia (Majeed and Breunig 2022; Department of Industry, Science, Energy and Resources 2016, 2021 and overseas (OECD 2018), and has been shown to have a strong link with productivity.

Table A1: Summary Statistics for Firm-Level Data

Full sample

Variables	Mean	Median	Share
Employment (FTE)	293	14	
Sales growth %	6	3	
Age	25	18	
Share innovating %			52
Share of firms >5 years old %			81
Share of firm finance access hampers innovation %			15
Share of SME %			78
Total observations '000s			103

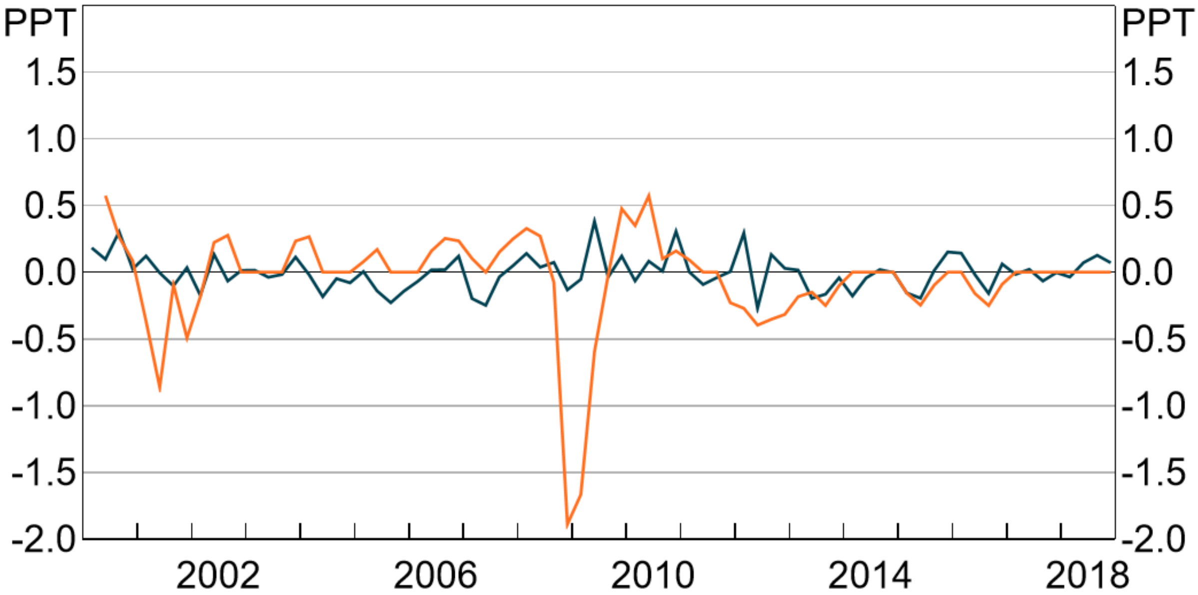
Source: ABS; Authors' calculations

Table A2: Summary Statistics for Firm-Level Data

	Mean	Median	Share	Mean	Median	Share
		SMEs firms			**Large firms**	
Employment (FTE)	22	8		1,246	569	
Sales growth %	6	3		8	4	
Age	21	15		44	31	
Share innovating %			48			63
Share of firms >5 years old %			78			90
Share of firm finance access hampers innovation %			17			8
Total observations '000s			80			20
		Non-exporters			**Exporters**	
Employment (FTE)	143	9		624	79	
Sales growth %	7	3		5	3	
Age	22	15		34	24	
Share innovating %			47			62
Share of firms >5 years old %			79			89
Share of firm finance access hampers innovation %			16			14
Total observations '000s			70			32
		Domestically owned			**Foreign owned**	
Employment (FTE)	136	10		906	355	
Sales growth %	6	3		6	4	
Age	23	16		35	23	
Share innovating %			50			60
Share of firms >5 years old %			81			85
Share of firm finance access hampers innovation %			17			10
Total observations '000s			81			21

Source: ABS; Authors' calculations

Figure A1: Monetary Policy Shock Measure

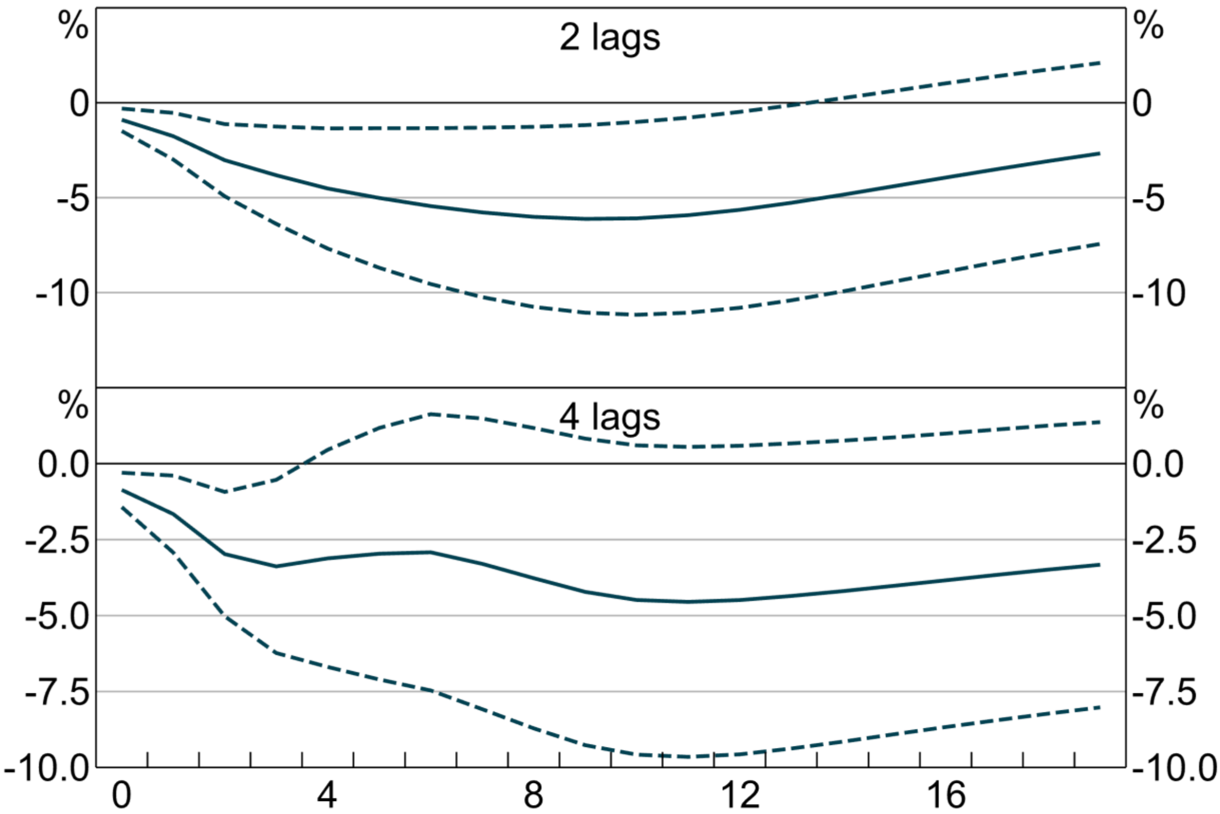


Note: Figure shows the change in the policy rate (orange) plotted against our preferred monetary policy shock measure (green). Quarter average measures.
Source: RBA; Beckers (2020)

Appendix B: Additional regression results

Figure B1: Effect of Monetary Policy Shock on R&D Spending in VAR Model

100 basis point shock, quarters



* Response from a VAR with log level of CPI, GDP, R&D, trade-weighted exchange rate and level of cash rate and shock. Response from Cholesky decomposition with shock measure ordered first. Dash lines are 90 per cent confidence intervals.

Source: Authors' calculations.

Note: Figure shows response of R&D spending to monetary policy shock in a VAR containing the log levels of the CPI, real GDP, real R&D spending, the trade-weighted exchange rate index, the level of the cash rate, and the Beckers (2020) shock. Response based on a Cholesky decomposition with the shock measure ordered first. Top panel is VAR(2) model. Bottom panel is VAR(4) model. Dashed lines are 90 per cent confidence intervals.

Table B1: Effect of 100 basis point shock on share of firms innovating

By firm size, cash rate change

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	-1.25*	0.03	0.38	1.25
(s.e.)	(0.65)	(0.92)	(0.64)	(1.20)
R^2	*0.20*	*0.14*	*0.11*	*0.09*
Observations	*45053*	*35,635*	*26,302*	*17,536*
SMEs				
Effect	-1.28	-0.29	-0.25	-0.64
(s.e.)	(0.83)	(1.06)	(0.80)	(1.27)
R^2	*0.19*	*0.13*	*0.12*	*0.10*
Observations	*29,551*	*22,185*	*14,616*	*7,291*
Large firms				
Effect	-1.03	0.48	1.05	2.50
(s.e.)	(0.91)	(1.19)	(0.85)	(1.73)
R^2	*0.19*	*0.11*	*0.07*	*0.06*
Observations	*15,502*	*13,450*	*11,686*	*10,245*

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Table B2: Effect of 100 basis point shock on share of firms innovating

By firm size, Beckers shock

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	-4.38**	-3.52**	-0.03	5.51**
(s.e.)	(1.49)	(1.55)	(2.06)	(2.26)
R^2	*0.05*	*0.05*	*0.05*	*0.04*
Observations	*45,151*	*35,705*	*26,342*	*17,545*
SMEs				
Effect	-5.60***	-6.44***	-3.87*	-0.93
(s.e.)	(1.44)	(1.13)	(1.84)	(1.67)
R^2	*0.05*	*0.05*	*0.05*	*0.05*
Observations	*29,648*	*22,255*	*14,656*	*7,300*
Large firms				
Effect	-1.37	1.01	3.84	10.48**
(s.e.)	(3.01)	(2.65)	(2.64)	(3.99)
R^2	*0.03*	*0.02*	*0.03*	*0.03*
Observations	*15,503*	*13,450*	*11,686*	*10,245*

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Table B3: Effect of 100 basis point shock on share of firms innovating

By firm size, BT shock

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	-1.75	-0.83	0.19	2.28
(s.e.)	(1.09)	(1.40)	(0.97)	(1.69)
R^2	*0.05*	*0.05*	*0.05*	*0.04*
Observations	*45151*	*35,705*	*26,342*	*17,545*
SMEs				
Effect	-2.51	-2.16	-1.51	-2.10
(s.e.)	(1.50)	(1.45)	(1.22)	(1.43)
R^2	*0.05*	*0.05*	*0.05*	*0.05*
Observations	*29,648*	*22,255*	*14,656*	*7,300*
Large firms				
Effect	-0.16	0.47	2.02*	4.94*
(s.e.)	1.18	1.90	1.09	2.46
R^2	*0.03*	*0.02*	*0.03*	*0.03*
Observations	*15,503*	*13,450*	*11,686*	*10,245*

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Table B4: Effect of 100 basis point shock on share of firms innovating

By firm size, levels shock

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	0.12	-0.18	-0.21	-0.39
(s.e.)	(0.26)	(0.42)	(0.25)	(0.44)
R^2	*0.05*	*0.05*	*0.05*	*0.04*
Observations	*45,151*	*35,705*	*26,342*	*17,545*
SMEs				
Effect	0.22	0.05	0.19	0.81
(s.e.)	(0.38)	(0.43)	(0.35)	(0.49)
R^2	*0.05*	*0.05*	*0.05*	*0.05*
Observations	*29,648*	*22,255*	*14,656*	*7,300*
Large firms				
Effect	-0.11	-0.37	-0.59*	-1.02
(s.e.)	(0.29)	(0.53)	(0.27)	(0.63)
R^2	*0.03*	*0.02*	*0.03*	*0.03*
Observations	*15,503*	*13,450*	*11,686*	*10,245*
Difference by size significant at	5 per cent level	1 per cent level	1 per cent level	10 per cent level

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Table B5: Effect of 100 basis point shock on share of firms innovating

By exporter status, SMEs

	Year 0	Year 1	Year 2	Year 3
Exporter				
Effect	-3.84	-3.29	-0.16	4.07
(s.e.)	(1.98)	(1.94)	(3.92)	(3.26)
R^2	*0.19*	*0.14*	*0.13*	*0.10*
Observations	*7,733*	*5,788*	*3,847*	*2,009*
Not exporter				
Effect	-2.24	-6.90***	-2.85	0.99
(s.e.)	(1.60)	(1.21)	(1.88)	(1.34)
R^2	*0.19*	*0.13*	*0.10*	*0.09*
Observations	*21,818*	*16,397*	*10,769*	*5,282*
Difference by exporter status significant at	N/A	N/A	N/A	N/A

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Table B6: Effect of 100 basis point shock on share of firms innovating

By exporter status, Large

	Year 0	Year 1	Year 2	Year 3
Exporter				
Effect	3.47	4.76	5.91*	9.73*
(s.e.)	(2.76)	(3.06)	(2.62)	(4.92)
R^2	*0.20*	*0.11*	*0.08*	*0.06*
Observations	*10,241*	*8,946*	*7,825*	*6,895*
Not exporter				
Effect	3.65	-1.49	3.12	9.79*
(s.e.)	(2.98)	(3.30)	(2.63)	(4.52)
R^2	*0.18*	*0.09*	*0.07*	*0.06*
Observations	*5,261*	*4,504*	*3,861*	*3,350*
Difference by exporter status significant at	N/A	10 per cent level	N/A	N/A

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Table B7: Effect of 100 basis point US shock on share of firms innovating

By export status, SMEs

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	-7.00	-10.33**	-9.85*	-21.19
(s.e.)	(4.52)	(3.80)	(5.22)	(16.05)
R^2	*0.19*	*0.14*	*0.12*	*0.10*
Observations	*29,551*	*22,185*	*14,616*	*7,291*
Exporters				
Effect	-11.44*	-11.76	-18.81**	-16.62
(s.e.)	(5.61)	(6.85)	(6.92)	(19.25)
R^2	*0.19*	*0.14*	*0.13*	*0.10*
Observations	*7,733*	*5,788*	*3,847*	*2,009*
Non-exporters				
Effect	-5.48	-9.59**	-6.93	-25.36
(s.e.)	(4.59)	(4.58)	(5.41)	(18.18)
R^2	*0.19*	*0.12*	*0.10*	*0.09*
Observations	*21,818*	*16,397*	*10,769*	*5,282*
Difference by size significant at	N/A	N/A	N/A	N/A

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Table B8: Effect of 100 basis point US shock on share of firms innovating

By export status, Large

	Year 0	Year 1	Year 2	Year 3
All firms				
Effect	-3.66	-11.49*	-5.59	-9.62
(s.e.)	(9.19)	(6.05)	(5.71)	(8.97)
R^2	0.19	0.11	0.07	0.06
Observations	15,502	13,450	11,686	10,245
Exporters				
Effect	-5.36	-10.66	-5.90	-12.94
(s.e.)	(9.22)	(6.44)	(7.54)	(10.87)
R^2	*0.20*	*0.11*	*0.08*	*0.06*
Observations	*10,241*	*8,946*	*7,825*	*6,895*
Non-exporters				
Effect	-0.14	-14.17	-5.39	-2.67
(s.e.)	(10.20)	(7.93)	(4.51)	(7.54)
R^2	*0.18*	*0.09*	*0.07*	*0.06*
Observations	*5,261*	*4,504*	*3,861*	*3,350*
Difference by size significant at	N/A	N/A	N/A	N/A

Note: Standard errors in parentheses, ***P < 0.01; **P < 0.05; *P < 0.1. Standard errors clustered at an annual level. Significance assessed using T-distribution with t-n degrees of freedom as suggests by Cameron and Miller (2015) to account for small number of clusters, where t is sample length and n is number of coefficients. All regressions include controls for industry, (lag) GDP growth, (lag) inflation, (lag) growth in the exchange rate, (lag) turnover growth and (lag) employment, and lag of the shock and dependent variable.

Source: Authors' calculations

Data disclaimer

The following data disclaimer should be noted: the results of these studies are based, in part, on Australian Business Registry (ABR) data supplied by the Registrar to the ABS under A New Tax System (Australian Business Number) Act 1999 and tax data supplied by the Australian Taxation Office (ATO) to the ABS under the Taxation Administration Act 1953. These require that such data are only used for the purpose of carrying out functions of the ABS. No individual information collected under the Census and Statistics Act 1905 is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes and is not related to the ability of the data to support the ABR's or the ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of these data have been followed. Only people authorised under the Australian Bureau of Statistics Act 1975 have been allowed to view data about any particular firm in conducting these analyses. In accordance with the Census and Statistics Act 1905, results have been rendered confidential to ensure that they are not likely to enable identification of a particular person or organisation.