A Granular View of the Australian Business Cycle*

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Abstract

We provide evidence supporting the hypothesis that idiosyncratic firm-level shocks are important drivers of the Australian business cycle (*granular hypothesis*). We first document that the distribution of firm size in Australia is substantially asymmetric and follows a Power law distribution with a long right tail. We then show that labour productivity shocks to the largest non-financial firms in Australia account for about 20% to 40% of the variation in Australian GDP growth for the period 2000–2018. Besides energy sector firms, firms in the construction, transportation and consumer services sectors appear to be relevant drivers of GDP growth.

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1 Introduction

Over the last decade, the hypothesis that business cycle fluctuations have a microeconomic source has gained popularity. Two features of the economy that support this view are: i) the asymmetric nature of the firm size distribution (see, for example, Gabaix (2011), Di Giovanni et al. (2014), Da-Silva et al. (2018) and Fornaro and Luomaranta (2018)), and ii) the asymmetric structure of the input–output connections (Acemoglu et al. (2012) and Dungey and Volkov (2018)). Importantly, in an economy where a few firms are disproportionally large or supply a disproportionally large share of intermediate inputs, firm-level shocks do not disappear, and instead are capable of generating the fluctuations typically observed in GDP.[1] This hypothesis, referred to as *granularity*, is appealing as it provides a microfoundation for the sources of aggregate productivity shocks, such that by studying the behaviour of relatively few individual firms, we can better infer the behaviour of the aggregate economy.

In this paper, we use firm-level data on labour productivity and revenue for large Australian companies—sourced from S&P market intelligence and Bloomberg—to investigate whether the granular hypothesis holds for the Australian economy. We first verify that the distribution of firm size in Australia is fat tailed and obeys a power law distribution.[2] We then construct a proxy for idiosyncratic shocks that affect large firms, in the spirit of Gabaix (2011), and show that about 20% to 40% of the fluctuations in Australian GDP growth between 2000-2018 are driven by shocks to large non-financial firms, mostly those in the energy, transportation, construction and consumer services sectors. Interestingly, the results indicate that non-energy and non-financial firms—for example, Qantas, Telstra, and Wesfarmers—play a relatively important role in accounting for the fluctuations in Australian GDP growth. Our results hold after controlling for monetary policy shocks, government spending shocks, aggregate uncertainty shocks, and fluctuations in the terms of trade and the real exchange rate.

We address our small sample size problem (we only have 17 years of labour productivity data) and reverse causality concern (that GDP instead drives firm productivity) through performing three validating exercises. First, we enlarge our sample size by using semi-annual data on companies' revenue growth from Bloomberg. The results with the extended sample

[1] The hypothesis postulated by Gabaix (2011) was previously disregarded by Lucas (1977) and Dupor (1999). These studies argue that by the law of large numbers, shocks to individual firms diversify away and therefore generate negligible aggregate effects. However, their findings only hold when firms are *quasi-symmetric* in size.

[2] Gabaix (2009) demonstrates that several economic variables follow a power law. That is, there is a non-negligible probability of finding very large cities, firms or stock price returns. To estimate the power law shape parameter, we follow Gabaix (1999).

(38 semesters of data) confirm the statistically significant relationship between large firms' innovations and aggregate GDP growth. Second, we show that the pairwise correlations between firm-level shocks are small and centred around zero. Therefore, we are confident that our measured firm-level shocks are not driven by aggregate shocks. Third, we perform a narrative analysis to make sense of the firm-level shocks. We identify a series of events affecting large Australian companies, including Qantas, Rio Tinto and Telstra, and verify that they correspond to our estimated firm-level shocks.

The results in this paper highlight the importance of deviating from the representative firm framework and instead consider firm-level heterogeneity in modelling the Australian macroeconomy. Our findings are also important for policy making in that monitoring and predicting the performance of large non-financial companies appears fundamental to predicting the evolution of Australian GDP growth.

Related literature: A few recent studies in the related literature support the hypothesis of granular business cycles. Using firm-level data, Gabaix (2011), Wagner (2012), Di Giovanni et al. (2014) and Fornaro and Luomaranta (2018) document for the U.S., Germany, France and Finland, respectively, that idiosyncratic disturbances to large firms can account for a sizable proportion of GDP fluctuations.[3] Besides focusing on Australia as a small open economy, the current analysis contributes to these previous studies by employing two different measures of firm-level shocks: innovations to labour productivity (Gabaix (2011)) and sales growth (Di Giovanni et al. (2014) and Fornaro and Luomaranta (2018)). In addition, we investigate in detail the degree of asymmetric distribution of firm-level sales in Australia. We estimate the power law shape parameter and show that the distribution of firm sales is extremely fat tailed. In addition, unlike previous studies that disregard the hypothesis of reverse causality—that aggregate shocks jointly drive GDP and firm-level labour productivity—we take advantage of the time-series properties of our shocks to prove that the pairwise correlation between firm-level shocks is centred around zero.

This paper also relates to Dungey et al. (2017). That study characterises systemically important companies in Australia by how connected they are to the rest of the economy, and places an emphasis on the role played by financial institutions and energy sector firms. We instead identify systemic companies as firms that represent a disproportionally large fraction of total revenues. Besides confirming the importance of financial and energy sector firms, we highlight the role of firms in other sectors of the Australian economy. Interestingly, we find that about 30% to 50% of the explanatory power of the granular residual of non-financial

[3] See also Lee (2015) and Ebeke and Eklou (2017).

firms is from shocks to companies in construction, transportation, telecommunication and consumer services.

The remainder of the paper is organised as follows. Section 2 provides the theoretical background for the analysis of the granular origins of business cycle fluctuations in Australia. Section 3 describes the data. Section 4, after demonstrating that the distribution of firm size in Australia has a clear right tail, measures the granular residual of the largest firms in Australia and estimates the empirical relationship between GDP growth and the shocks received by these firms. Section 5 performs two validating exercises to support our regression results further. Section 6 concludes.

2 Theoretical Background

Suppose the economy is populated by N firms. Each firm i produces s_{it} units of a homogeneous good at time t. Production is exogenous and does not require intermediate inputs. The growth rate of firm i's production is given by:

$$\frac{\Delta s_{i,t+1}}{s_{it}} = \frac{s_{i,t+1} - s_{i,t}}{s_{it}} = \sigma_i \varepsilon_{i,t+1},$$

where σ_i is the volatility of firm i and $\varepsilon_{i,t+1}$ is an independently and identically distributed (iid) shock that affects firm i's production. $\varepsilon_{i,t+1}$ has zero mean and unit variance. GDP in this economy is:

$$GDP_t = Y_t = \sum_{i=1}^{N} s_{it},$$

while GDP growth is:

$$\%\Delta GDP_t = \frac{1}{Y_{t-1}} \sum_{i=1}^{N} \Delta s_{i,t} = \sum_{i=1}^{N} \sigma_i \left(\frac{s_{it-1}}{Y_{t-1}} \right) \varepsilon_{i,t}, \tag{1}$$

where the last term is the so-called *granular residual*. Equation (1) reveals that the weighted sum of firm-level disturbances drives aggregate fluctuations. We can then use the fact that firm-level shocks ($\varepsilon_{i,t}$) are iid and have unit variance to express the standard deviation GDP growth (σ_{gdp}) as:

$$\sigma_{gdp} = \left(\sum_{i=1}^{N} \sigma_i^2 \left(\frac{s_{it-1}}{Y_{t-1}} \right)^2 \right)^{1/2},$$

where the aggregate importance of a given firm's volatility on aggregate volatility is determined by the relative size of the firm ($\frac{s_{it-1}}{Y_{t-1}}$). Suppose, for exposition, that shocks to all firms have the same volatility $\sigma_i = \sigma$, for all i. Then, the standard deviation of GDP growth can be expressed as:

$$\sigma_{gdp} = \sigma \left(\sum_{i=1}^{N} \left(\frac{s_{it}}{Y_t} \right)^2 \right)^{1/2} = \sigma h, \tag{2}$$

where h is the well-known Herfindahl index of the economy, which is typically used to measure the extent of concentration in a given market. Lucas (1977) and Dupor (1999) were the main critics of the hypothesis of the granular origins of aggregate fluctuations as they argued that with *diversification* the shocks to individual firms would wash out as the number of firms increases. Their argument can be exposed using a simple example. Suppose every firm represents the same fraction of total production, $\frac{s_{it}}{Y_t} = \frac{1}{N}$. In this case, Equation (2) becomes:

$$\sigma_{gdp} = \frac{\sigma}{\sqrt{N}},$$

implying that when N approaches infinity, firm-level disturbances will be "averaged out" and therefore not generate any sizable aggregate effects. Indeed, aggregate volatility approaches zero according to $\frac{1}{\sqrt{N}}$. However, as Gabaix (2011) demonstrates, the diversification argument does not hold when the distribution of firm size follows a power law. Indeed, as we show later, the data for Australia largely supports the power law distribution of firm size.

3 Data and Summary Statistics

3.1 Macro-level data

We use two measures of aggregate activity for the Australian economy at the annual frequency: real and per capita GDP growth. Both measures are sourced from the World Development indicators (WDI). [4] Figure 1 plots GDP growth since 1984. As shown by both measures, we observe three periods of marked decline in economic activity, comprising the downturns of the early 1990s, the downturn of the early 2000s and the global financial crisis (GFC) in 2008–2009.

Table 3.1 provides descriptive statistics of GDP growth for Australia between 1984 and 2017. Both measures of growth display very similar volatility. The standard deviation of real GDP growth is 1.27%, while the standard deviation of per capita GDP growth is 1.34%.

[4] See http://datatopics.worldbank.org/world-development-indicators/

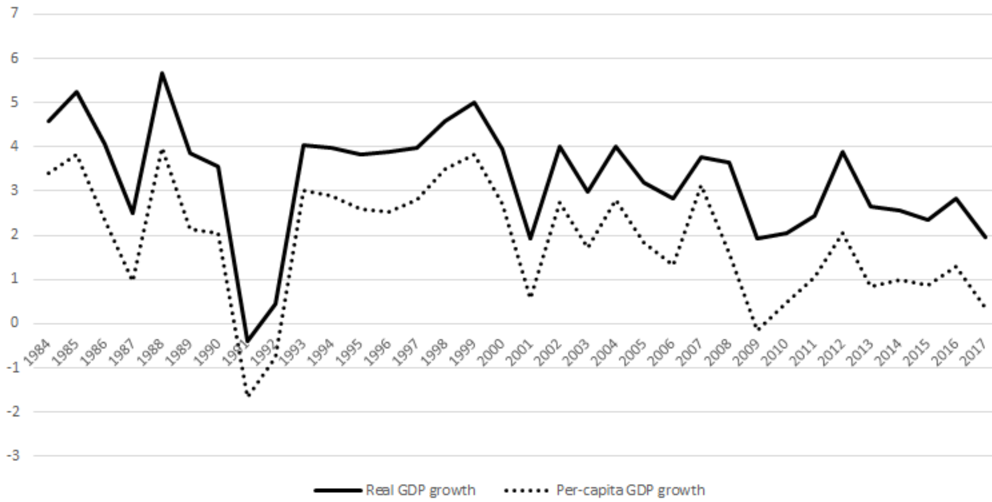

Figure 1
Australian GDP growth, 1984–2017

Table 3.1
Summary statistics of Australian GDP growth, 1984–2017

Variables	Num. Years	Mean	S.D.	Min	Max
Real GDP growth	34	3.28%	1.27%	-0.38%	5.68%
Per capita GDP growth	34	1.87%	1.34%	-1.64%	3.96%

3.2 Micro-level data

Our firm-level data is sourced from S&P Global Market Intelligence. This data includes annual information on revenues and employees for more than 1,000 publicly listed companies in Australia since 1990. However, as the number of firms with missing revenue data is not small, especially for the period 1990–1998, our sample covers the period 1999–2017, which is the period with the most comprehensive firm-level data. In terms of representativity of the Australian economy, while our employment data covers only a 0.0042% (103/2,425,818) of companies registered in Australia at December 2016, because the sample is biased towards large firms our data covers a 5.2% of total employment in Australia (624,654/11,949,300).[5]

Table 3.2 presents descriptive statistics of all firms in the sample with valid data for total revenue and total employees in Australia in 2016. There are 1,198 public companies with non-missing revenue data. As shown, average revenue (468.2 U.S. million dollars) is about

[5]The number of registered companies is obtained from the report "AUSTRALIAN JOBS 2017" prepared by the Australian Department of Employment. In terms of non-missing revenue data, our sample covers a 0.5% of Australian companies (1198/2,425,818).

70 times larger than median revenue, which is evidence of the existence of extremely large firms. There are only 103 firms with non-missing data on the total number of employees. The average size is 5,877 employees, while the median firm has 382 employees. The last row displays the distribution of firm revenue for the smaller group of companies with non-missing data on total employees. Clearly, the subsample of firms with information on the number of employees is biased towards larger firms (see Table 6.1 in the Appendix for more details). This is especially useful for our purposes as we can construct a time series for labour productivity (revenue/employees) for very large companies, as these arguably drive the fluctuations in aggregate GDP.

Table 3.2
Revenue and employee summary statistics, 2016

Variables	Num. firms	Mean	p25	p50	p75	p95
Revenue	1,198	468.2	0.224	6.42	105.8	1,809
Employee	103	5,877	78	382	2,215	32,551
Revenue	103	2,160	10.4	122.15	633.6	11,348

Note: The data is sourced from S&P Global Market Intelligence. The unit for revenue is millions of U.S. dollars.

The descriptive statistics for previous years are similar to those in Table 3.2. The number of firms with non-missing data on employees is again small, but these firms are among the largest companies in the sample. Therefore, problems with missing data do not prevent us from studying the granular hypothesis. In the rest of the paper, we use the raw data in U.S. dollars each year, but the same results hold when we convert U.S. dollars to Australian dollars.

4 Testing the Granular Hypothesis

In this section, we begin by documenting the asymmetric nature of firm size in Australia. We then measure shocks to large firms. Equipped with large firm shocks, we construct the granular residual for the top K companies in Australia. Next, we estimate an OLS regression specifying GDP growth as the dependent variable and the granular residual as the primary independent variable. Our specification also controls for aggregate movements in commodity prices, oil prices, cash rate, terms of trade, real exchange rate, real government spending, and the real cash rate.

4.1 Firm size distribution

As emphasised in the theoretical section, the empirical plausibility of the granular hypothesis relies on a sufficiently right-tailed distribution of firm size. In such a world, shocks that affect large companies have sizable aggregate effects. More formally, Gabaix (2011) showed that if the distribution of firm size follows a power law, the law of large numbers does not apply (the so-called diversification argument), implying that firm-level shocks are capable of generating sizable aggregate effects. We now proceed to estimating the power law parameter of the firm size distribution in Australia. Suppose that the probability of finding a firm size S_i larger than s is described by the following power law distribution:

$$P(S_i > s) = \kappa s^{-\xi}, \tag{3}$$

where ξ is known as the power law shape parameter and κ is some constant. A fat-tailed distribution is given by $0 \leq \xi \leq 2$. The smaller the value of ξ, the greater the probability of observing extremely large firms. A value of $\xi = 1$ corresponds to Zipf's law highlighted by Gabaix (1999). We follow Gabaix (1999) and estimate the shape parameter ξ by regressing:

$$\log(rank - 1/2) = \log\kappa + \beta \log s, \tag{4}$$

where the *rank* is calculated based on the firms' revenues s.[6] The estimated coefficient β is expected to be negative and the value of ξ is the absolute value of β. As discussed, the smaller the value of ξ, the greater the probability of finding very large firms. Given that the power law distribution is generally not a good description of the distribution of small firms, we follow Gabaix (2009), Levy (2009) and Di Giovanni et al. (2011) and estimate the regression after removing those small firms below certain cut-offs of annual revenue.[7]

Table 4.1 presents the OLS estimates of Equation (4) using sales and sales rank in 2006. Every column represents a different sample that uses a different cut-off to remove small firms. In all columns, the absolute value of the coefficient is relatively small with the range [0.41, 1.02]. The coefficients are also very precisely estimated, with standard errors in the range [0.014, 0.073]. The R^2 of the regression is very large, especially in columns 2 to 4, indicating a very good fit of the power law distribution in characterising the right tail of firm

[6] We follow Gabaix and Ibragimov (2011) and use $\log(rank - 1/2)$ instead of $\log(rank)$ to correct for the small sample bias in the estimation of β in Equation (4).

[7] Gabaix (1999) shows that for 135 U.S. metropolitan areas, the log of population against the log rank follows Zipf's law almost exactly.

Table 4.1
Log rank vs. log revenue, 2006

	(1)	(2)	(3)	(4)
VARIABLES	log rank06	log rank06	log rank06	log rank06
Log revenue 2006	-0.410***	-0.677***	-0.908***	-1.024***
	(0.014)	(0.033)	(0.057)	(0.073)
Observations	464	164	77	54
R-squared	0.898	0.930	0.933	0.930

* Note: This table presents the OLS coefficients of regressing $\log(rank - 1/2)$ against log revenues in 2006. Columns 1, 3, 4 and 5 retain firms with revenues exceeding 1.45, 100, 500 and 1,000 U.S. million dollars, respectively. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

size. Moreover, the power law parameter converges to Zipf's law ($\xi = 1$) when the sample is restricted to larger firms (Gabaix (1999)).

Table 4.2 reports the OLS coefficients of estimating Equation (4) using sales in 2016; very similar results hold. The power law parameter is small and precisely estimated. It also converges to one once the sample is restricted to larger firms.

While the results in Tables 4.1 and 4.2 show strong support for the Zipf's law ($\xi = 1$), they also suffer from the critic in Eeckhout (2004), who argues that the "global" Zipf's law in the data is sensitive to the truncation point of the sample. The sensitivity to the truncation point is clear in Tables 4.1 and 4.2. Eeckhout (2004) claims that the Zipf's law observed in the right tail of cities is simply arising from an underlying lognormal distribution for the whole sample of cities.[8] Levy (2009) reconciles the apparent inconsistency between Eeckhout (2004) and Gabaix (1999) by showing that while a lognormal distribution can fit very well most of the empirical distribution of city size, it cannot match well the upper-right tail of the distribution. Levy (2009) shows that the lognormal distribution heavily underestimates the number of very large cities and that a $\chi(2)$ test strongly rejects the lognormal distribution as a description of the right tail of cities.

[8] The lognormal distribution naturally displays a right-tail.

Table 4.2
Log rank vs. log revenue 2016

VARIABLES	(1) log rank16	(2) log rank16	(3) log rank16	(4) log rank16
Log revenue 2016	-0.418***	-0.697***	-0.910***	-1.049***
	(0.012)	(0.024)	(0.045)	(0.058)
Observations	720	301	125	87
R-squared	0.872	0.947	0.939	0.947

* Note: This table presents the OLS coefficients of regressing $\log(rank - 1/2)$ against log revenues in 2016. Columns 1, 3, 4 and 5 retain firms with revenues exceeding 1.45, 100, 500 and 1,000 U.S. million dollars, respectively. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We replicate Levy (2009)'s test to show that a lognormal distribution heavily under-predicts the thick of the right tail of the distribution of firm size. We focus on the 25% of largest firms in our sample and fit a lognormal distribution through maximum likelihood. The mean and standard deviation of log(revenue 2016) are $\mu = 6.27$ and $\sigma = 1.38$, respectively. The expected number of firms larger than $\mu + 3\sigma$ (log (revenue 2016)$= 10.39$) is $(1 - 0.99865) \cdot 301 = 0.406$, while in the data there are 4 firms larger than log (revenue 2016)$= 10.39$. As in Levy (2009), a statistical test strongly strongly rejects the lognormal distribution as a good representation of large firms' distribution in Australia.[9]

The good fit of the Pareto distribution in describing large firms in Australia is in Figure 2. We show a scatter plot of the observed log (rank -1/2)-log (revenue) data in 2016, and the implied log (rank -1/2)-log (revenue) relationship estimated in Table 4.2, column 4. While the Pareto fit is very inaccurate for firms with log revenue below 7, it fits very well the distribution of firms with revenues greater than 1,000 US million dollars.

The evidence in this section proves that the distribution of firm size in Australia is substantially asymmetric and well described by a power law distribution with a fat right tail (and a small value of ξ). This result is the basis for our study, as it provides the potential for the granular origins of aggregate fluctuations in the Australian economy. In the following section, we define our measure of large firm shocks, the so-called "granular residual". We

[9]The z test takes a value of 30.1 while the $\chi^2(1)$ critical value is 6.3.

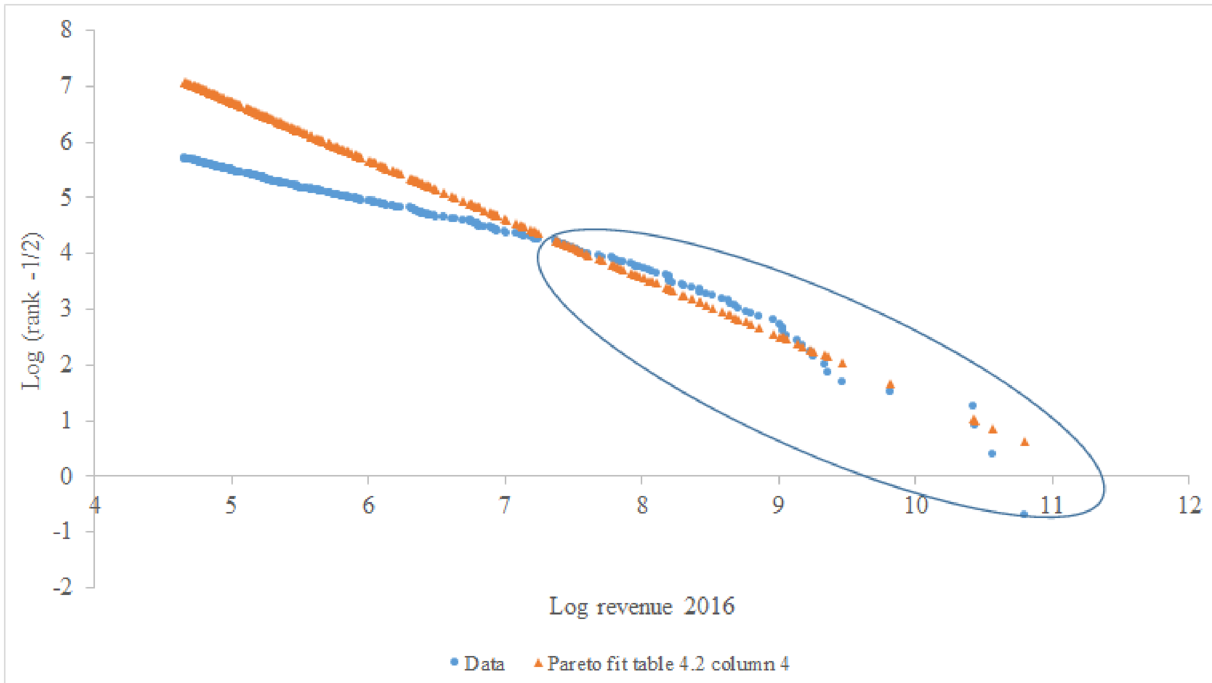

Figure 2
Pareto fit of the right-tail

then examine the importance of the granular residual in driving aggregate GDP growth.

4.2 The granular residual

The first task is to measure firm-level disturbances. To do this, we use a version of Equation (1). GDP growth is described by:

$$\Delta \log GDP_t \approx \sum_{i=1}^{K} \sigma_i \left(\frac{s_{it-1}}{GDP_{t-1}} \right) \varepsilon_{it} + \nu_t = \Gamma_t^K + \nu_t, \tag{5}$$

where GDP_t is real GDP at time t, s_i is firm i's real revenue, deflated using the GDP deflator (base year 1999), $\Gamma_t^K = \sum_{i=1}^{K} \sigma_i \left(\frac{s_{it-1}}{Y_{t-1}} \right) \varepsilon_{it}$ is the granular residual of the top K firms and ν_t is the error term. Note that the summation goes from $i = 1$ to K, where $K < N$ is the subsample of large firms considered in our analysis. Without loss of generality, suppose that $\sigma_i = 1$ for all i. Therefore, aggregate GDP growth is determined by shocks ε_{it} affecting the largest K companies in the economy, as weighted by their size.

Our next goal is to measure the shocks affecting large firms. Unfortunately, our micro-data is not sufficiently rich to estimate the firm-level total factor productivity shocks. However, we do have information on labour productivity. Thus, we follow Gabaix (2011) and measure innovations to the labour productivity of large firms. Let us define labour productivity Z_{it} as the ratio:

$$Z_{it} = \frac{revenue_{it}}{employee_{it}}.$$

We then define g_{it} as the growth rate of firm-level productivity

$$g_{it} = \log Z_{it} - \log Z_{it-1}.$$

Now, suppose that firm-level labour productivity follows

$$g_{it} = \beta' X_t + \mu_{it},$$

where the X_t is a vector of aggregate factors that affects labour productivity growth at time t, while μ_{it} represents firm idiosyncratic disturbances. To control for aggregate factors affecting the labour productivity growth of all firms, we follow Gabaix (2011) and Di Giovanni et al. (2014) and assume that:

$$\widehat{\beta}' X_t = \frac{1}{Q} \sum_{i=1}^{Q} g_{it} = \bar{g}_t,$$

where Q corresponds to the number of firms in our sample with non-missing data on labour productivity in a given year. We essentially de-mean firm-level productivity growth to remove any aggregate shocks affecting all firms equally. Our primary goal is to inspect the relationship between $\hat{\mu}_{it}$, the individual component of large firm shocks, and aggregate GDP. Thus, we define the estimated granular residual $\hat{\Gamma}_t$ for the largest K firms as

$$\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{revenue_{i,t-1}}{GDP_{t-1}} \hat{\mu}_{it} = \sum_{i=1}^{K} \frac{revenue_{i,t-1}}{GDP_{t-1}} (g_{it} - \bar{g}_t). \tag{6}$$

To measure $\hat{\Gamma}_t$, we rank firms according to their 2016 sales. Our benchmark results consider the largest $K = 100$ companies. Given that not all the top-100 firms in terms of sales have data on labour productivity, we effectively consider about 20 of the top-100 firms with data on labour productivity.

Table 4.3 provides more detailed information on the largest firms in 2016. Our sample of large firms–those with information available on labour productivity–produce in 10 different sectors of the economy. We aggregate economic sectors with only one firm into the *Other*

Table 4.3
Top-100 firms in 2016

Sector	Revenues 2016 (mill. U.S dollars)	No. of firms	% total revenue
Construction	22054.1	3	11.25%
Consumer service	7190.2	2	3.67%
Energy	55906.6	5	28.53%
Financial	25606.5	3	13.07%
Transportation	13887.1	3	7.08%
Other sectors	71263.3	5	36.37%

sectors category.[10] Of these, energy sector firms represent the largest share of largest firms revenue (28%). However, firms in the financial (13%), construction (11%) and transportation (7%) sectors are also important actors.

We proceed to consider the co-movement between real GDP growth and the granular residual. Figure 3 plots the time series of annual GDP growth and the top-100 granular residual (as adjusted by its standard deviation and excluding financial institutions) since 2000. As depicted, there is strong co-movement between the series, evidenced by a correlation of 0.41 for the whole sample period (2000–2017) and 0.45 for the years prior to the GFC.

4.3 Regression results

We now analyse more formally whether the shocks to large firms–as summarised by the granular residual–are capable of generating sizable fluctuations in aggregate GDP growth. Our empirical specification is:

$$\Delta \log(GDP_t) = \alpha_0 + \sum_{i=0}^{L} \beta_i \hat{\Gamma}_{t-i} + \gamma Controls + e_t, \tag{7}$$

where β_i measures the effect of the granular residual in period $t-i$ on GDP growth at time t. To control for aggregate shocks, we include as covariates the growth rate of the terms of trade, the growth rate of the real exchange rate, monetary policy shocks, government spending shocks, and uncertainty shocks. The error term is e_t, which is assumed to be iid

[10] Among the other sectors category, Telstra (in the telecommunications sector) and Wesfarmers (in the retail and consumer service sector) are the largest firms.

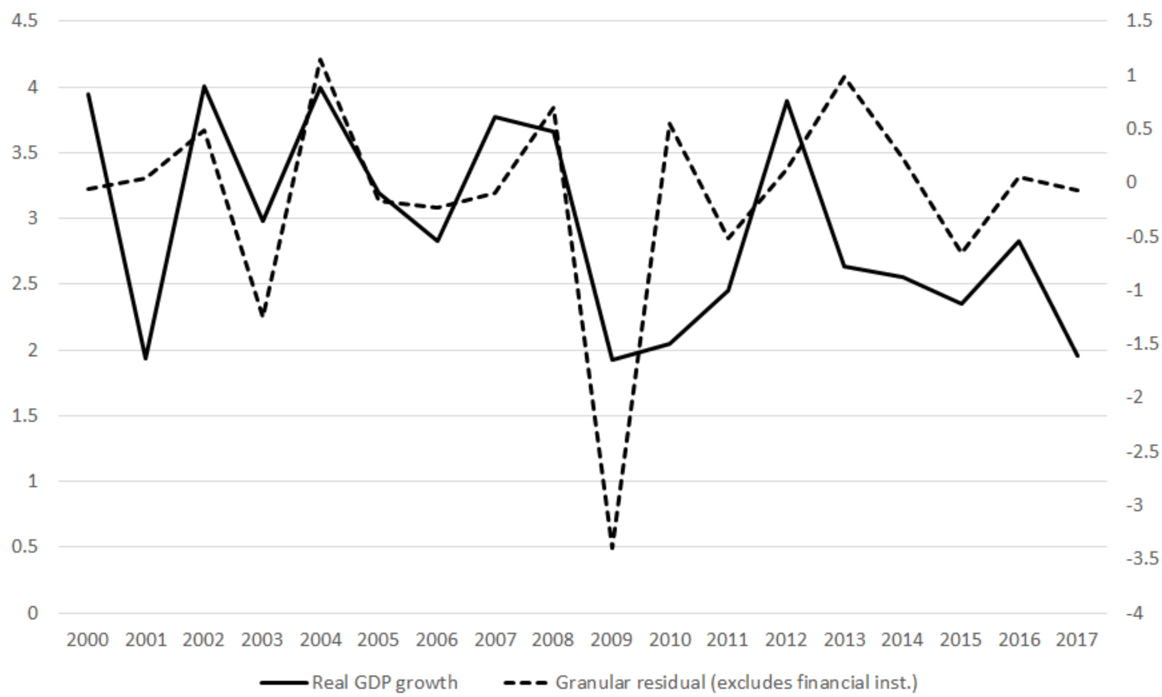

Figure 3
GDP growth and the granular residual (excluding financial institutions)

normal.[11] To simplify the interpretation of our results, we normalise the granular residual and other controls by their sample standard deviation. Therefore, β_i can be interpreted as the impact on GDP growth of a one-standard deviation change in the granular residual of large firms at time $t-i$.

We acknowledge the limitations of our regression analysis. Establishing a causal link from firm-level disturbances to aggregate activity is an ambitious task. Besides, the firm-level data on Australian firms available to non-government researchers only consists of comprehensive data over 17 years. In the next section, we enlarge our sample using semi-annual data on firm revenue growth from Bloomberg. In addition, we perform a series of validating exercises in Section 5 that aim to support the hypothesis that firm-level shocks drive an important share of GDP fluctuations.

Table 4.4 presents the regression results of our model without controlling for aggregate macroeconomic conditions. We consider three different measures of the granular residual and two different measures of GDP growth. $\hat{\Gamma}_t$ is the granular residual with all of the largest

[11] Same results hold when we control for the growth rate of oil prices, the growth rate of commodity prices, and the cash rate in nominal terms.

firms. $\hat{\Gamma}_t^E$ only contains energy sector firms, and $\hat{\Gamma}_t^{noF}$ excludes financial institutions. In columns 1 to 3, we specify real GDP growth as the dependent variable, while columns 4 to 6 employ per capita GDP growth.

Even though there is only a small sample over 17 years, the findings strongly support the granular hypothesis. The coefficient of the contemporaneous adjusted granular residual is positive and statistically significant at the 1% or 5% level for the three measures of $\hat{\Gamma}_t$, regardless of the GDP growth definition used. The results are also economically significant. A one-standard deviation increase in the granular residual leads to an increase in GDP growth of 0.35 to 0.48 percentage points, depending on the measure of growth employed. In addition, the granular residual itself accounts for 19% to 24% of the fluctuations in aggregate GDP growth observed between 2000–2017.

Our results in column 2 confirm the importance of energy sector firms ($\hat{\Gamma}_t^E$) in the Australian economy (Dungey et al. (2017)). In column 3, we check that our results are not driven by the inclusion of financial institutions. Indeed, the granular residual that excludes financial institutions ($\hat{\Gamma}_t^{noF}$) presents the largest R^2. This result is reassuring, as our measure of firm-level shocks might not be suitable for firms in the financial sector such as banks or insurance companies. We find that non-energy (and non-financial) firms account for a sizable fraction of aggregate fluctuations. The difference between the R^2 in columns (2) and (3) provides an indication of the additional predictive power of construction, transportation and consumer service firms. The R^2 increases by 0.055, implying that non-financial and non-energy firms account for 22% (0.055/0.242) of the fit of the non-financial granular residual ($\hat{\Gamma}_t^{noF}$).

As a robustness check, Table 6.4 in our Appendix illustrates the results of estimating Equation (7) using demeaned sales growth, instead of demeaned labour productivity, to construct the granular residual. The same results hold. The estimated coefficient of the three different measures of the granular residual are positive and statistically significant at the 95% confidence, for both growth measures. The estimates are also economically significant and the R^2 of the regressions are even larger compared to Table 4.4. In the Appendix, we also show that our results do not depend on the value of K. The same findings hold if we use $K = 200$ instead (see Table 6.3). The rest of this section uses labour productivity to construct the granular residual. In the next section, we use semi-annual revenue growth data to validate our findings with a larger sample.

We now proceed to control for macroeconomic shocks.[12] To account for the effect of

[12]Our macroeconomic data is sourced from the Reserve Bank of Australia Statistical Releases and the

commodity and oil prices we use the growth rate of terms of trade. We also control for changes in Australian real exchange rate. To control for monetary policy shocks, we use the estimated monetary policy shocks for Australia in Bishop and Tulip (2017).[13] The authors use the Romer and Romer (2004) approach to estimate monetary policy surprises. To control for fiscal policy we estimate government spending shocks using a recursive VAR approach as in Miranda-Pinto et al. (2019).[14] Finally, we control for aggregate uncertainty following Moore (2017). The author constructs an index of aggregate uncertainty for Australia using stock market volatility data. We update the index in Moore (2017) and estimate uncertainty shocks with a recursive VAR approach.[15] In Table 6.2 of our Appendix, we provide detailed descriptive statistics of our full set of control variables. We normalise our control variables using their sample standard deviation in Table 6.2.

Table 4.5 provides the results of estimating Equation (7) including the controls.

Our main result remains when using the controls. More importantly, compared with the importance of aggregate shocks, firm-level idiosyncratic shocks (as summarised by the granular residual) account for a sizable share of GDP fluctuations. Judging by the incremental effects on the R^2, the granular residual has a predictive power that is 7 times larger than the predictive power of all controls together. Similar to the results in Table 4.4, while large energy sector firms are important drivers of GDP growth, shocks that affect large firms in the construction, transportation and consumer service sectors are also important drivers of economic growth. The R^2 of the regression using the granular residual of non-financial firms (column 4) is 1.6 times larger than the R^2 of using the energy firms granular residual (column 3). In particular, non-financial and non-energy firms account for 38% ((0.5-0.309)/0.5) of the fit of the non-financial granular residual ($\hat{\Gamma}_t^{noF}$). The economic importance of the granular

Australian Bureau of Statistics.

[13]We are extremely grateful to Benjamin Becker who provided Bishop and Tulip (2017)'s updated monetary policy shocks series. The updated estimates have small differences with respect to the original estimates as the estimation sample starts in 1994 rather than in 1991 (which used interpolated inflation forecasts).

[14]The authors follow the Blanchard and Perotti (2002) and estimate a recursive VAR (4 lags) with log government spending, log real GDP, and interest rate for Australia (and all other OECD countries) for the period 1960Q1-2018Q4. By ordering government spending first, the authors assume that government spending is independent of contemporaneous macroeconomic conditions and only responds to contemporaneous government spending shocks.

[15]We update the forward-looking aggregate uncertainty index in Moore (2017) for years 2015-2018 using the realised volatility of ordinaries index, which is simple to calculate and highly correlated with his forward-looking measure. The realised volatility index is measured by semi-annual (annual) average of the daily absolute percentage change in the All Ordinaries index. Our data is sourced from Bloomberg. Our recursive VAR includes the log aggregate uncertainty index (ordered first), log real GDP, log private consumption, and the cash rate for the period 1987Q1-2018Q4.

Table 4.4
Granularity in Australia (Top-100)

VARIABLES	(1) RGDP	(2) RGDP	(3) RGDP	(4) pcGDP	(5) pcGDP	(6) pcGDP
$\hat{\Gamma}_t$	0.38***			0.46**		
	(0.125)			(0.162)		
$\hat{\Gamma}_t^E$		0.35***			0.45***	
		(0.109)			(0.143)	
$\hat{\Gamma}_t^{noF}$			0.40***			0.48**
			(0.125)			(0.162)
Observations	17	17	17	17	17	17
R-squared	0.231	0.187	0.242	0.224	0.206	0.235

* Note: This table presents the OLS coefficients from regressing GDP growth (real GDP and per-capita GDP) against the top-100 granular residual and its own lag. In columns 1 to 3, the dependent variable is real GDP growth, while in columns 4 to 6, the dependent variable is per capita GDP growth. $\hat{\Gamma}_t$ is the granular residual with all of the largest firms. $\hat{\Gamma}_t^E$ only contains energy sector firms, while $\hat{\Gamma}_t^{noF}$ excludes financial institutions. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

residual increases when considering the macroeconomic controls. A one-standard deviation increase in the granular residual of non-financial firms is associated with an increase in real GDP growth of 1.04 percentage points.

4.4 Extended sample: Bloomberg revenue data

As previously discussed, one problem with the results in Tables 4.4 and 4.5 is the small sample size. In this section, we use semi-annual data on firm-level revenue (converted to real, base year 1999) from Bloomberg to more than double the number of periods in our analysis. We redefine Z_{it} as

$$Z_{it} = revenue_{it},$$

and keep the same definition of g_{it} and Γ_{it} in Equation (6). While demeaned firm-level revenue growth is an imperfect proxy for firm-level shocks, it is the baseline measure for

Table 4.5
Granularity in Australia (Top-100, with controls)

VARIABLES	(1) RGDP	(2) RGDP	(3) RGDP	(4) RGDP
$\hat{\Gamma}_t$		0.81***		
		(0.244)		
$\hat{\Gamma}_t^E$			0.70*	
			(0.339)	
$\hat{\Gamma}_t^{noF}$				1.04***
				(0.224)
$\Delta \log RER$	-0.18	0.47	0.37	0.68**
	(0.201)	(0.301)	(0.408)	(0.296)
$\Delta \log TT$	0.17	0.04	-0.01	-0.06
	(0.248)	(0.244)	(0.264)	(0.232)
MP shocks	0.01	0.16	0.13	0.22
	(0.258)	(0.252)	(0.268)	(0.254)
G shocks	-0.15	-0.05	-0.08	0.04
	(0.226)	(0.202)	(0.243)	(0.196)
Uncert. shocks	-0.02	0.32	0.22	0.38*
	(0.225)	(0.186)	(0.219)	(0.178)
Observations	17	17	17	17
R-squared	0.057	0.417	0.309	0.500

* Note: This table presents the OLS coefficients of regressing real GDP growth against the top-100 granular residual and its own lag. It also controls for monetary policy shocks (MP shocks), government spending shocks (G shocks), stock market volatility shocks (Uncert. shocks), growth rate of real exchange rate (RER), and th growth rate of the terms of trade (TT). $\hat{\Gamma}_t$ is the granular residual with all of the largest firms. $\hat{\Gamma}_t^E$ contains only energy sector firms, while $\hat{\Gamma}_t^{noF}$ excludes financial institutions. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

firm-level disturbances in Di Giovanni et al. (2014) and Fornaro and Luomaranta (2018). Our new sample starts in year 2000 semester 1 and ends in year 2018 semester 2 (38 periods). To obtain higher frequency real GDP growth data, we collect quarterly real GDP growth (seasonally-adjusted) data from the Australian Bureau of Economics.[16]

The results in Table 4.6 are consistent with our baseline regression results in Tables 4.4 and 4.5. In column 1, we can see that a one-standard deviation increase in the granular residual increases real GDP growth by 0.15 percentage points (at the semi-annual frequency). This result is statistically significant at the 99% of confidence and it is also economically important. As in Table 4.5, the sole inclusion of the granular residual significantly increases the R^2 of the regression (from 0.12 to 0.4). Columns 2 and 3 also indicate that non-energy sector firms and non-financial sector firms are important in accounting for GDP fluctuations in Australia. In this case, a 50.5% ((0.265-0.131)/0.265) of the regression fit in Table 4.6 column 4 is accounted by non-financial and non-energy sector firms.

5 Validating Exercises

In this section, we perform two approaches to support the idea that firm-level disturbances, not the reverse, drive aggregate GDP. The first approach considers the pairwise correlations of our measure of large firm shocks. The second is a narrative approach that links firm-specific episodes, such as changes in CEO, regulatory problems and natural disasters, to the firms' labour productivity shocks measured in Section 4.

5.1 How idiosyncratic are firm-level shocks?

As discussed, our results could suffer from reverse causality, namely that if an aggregate shock drives aggregate GDP and firm productivity, it is natural to observe a positive correlation between the granular residual and GDP growth. To rule out reverse causality, we examine the pairwise correlation between firm-level shocks for the largest non-financial firms. The average pairwise correlation of firm-level shocks affecting the top-20 firms in our sample (excluding financial institutions) is 0.08, which is significantly small. Figure 4 displays a histogram of the pairwise correlation of firm-level shocks. The pairwise correlations are distributed around zero, with more than 70% of the correlations lying between -0.37 and 0.56. Of course, while the evidence presented in Figure 4 is only suggestive, it is reasonably strong to disregard

[16] https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5206.0Mar%202019?OpenDocument

Table 4.6
Granularity in Australia: Semi-annual revenue growth

VARIABLES	(1) RGDP	(2) RGDP	(3) RGDP	(4) RGDP
$\hat{\Gamma}_t$		0.15***		
		(0.042)		
$\hat{\Gamma}_t^E$			0.03	
			(0.076)	
$\hat{\Gamma}_t^{noF}$				0.13**
				(0.058)
$\Delta \log RER$	0.08	0.14**	0.08	0.11
	(0.078)	(0.059)	(0.077)	(0.063)
$\Delta \log TT$	-0.06	-0.08	-0.08	-0.09*
	(0.040)	(0.045)	(0.070)	(0.050)
MP shocks	-0.01	-0.08	-0.02	-0.04
	(0.062)	(0.060)	(0.067)	(0.065)
G shocks	0.07	0.10*	0.07	0.08
	(0.055)	(0.053)	(0.069)	(0.053)
Uncert. shocks	-0.07	-0.05	-0.08	-0.09
	(0.072)	(0.066)	(0.080)	(0.069)
Observations	38	38	38	38
R-squared	0.123	0.395	0.131	0.265

* Note: This table presents the OLS coefficients of regressing real GDP growth against the top-100 granular residual and its own lag. It also controls for monetary policy shocks (MP shocks), government spending shocks (G shocks), stock market volatility shocks (Uncert. shocks), growth rate of real exchange rate (RER), and th growth rate of the terms of trade (TT). $\hat{\Gamma}_t$ is the granular residual with all of the largest firms. $\hat{\Gamma}_t^E$ contains only energy sector firms, while $\hat{\Gamma}_t^{noF}$ excludes financial institutions. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

reverse causation and the existence of common shocks jointly driving GDP growth and large firm labour productivity disturbances.

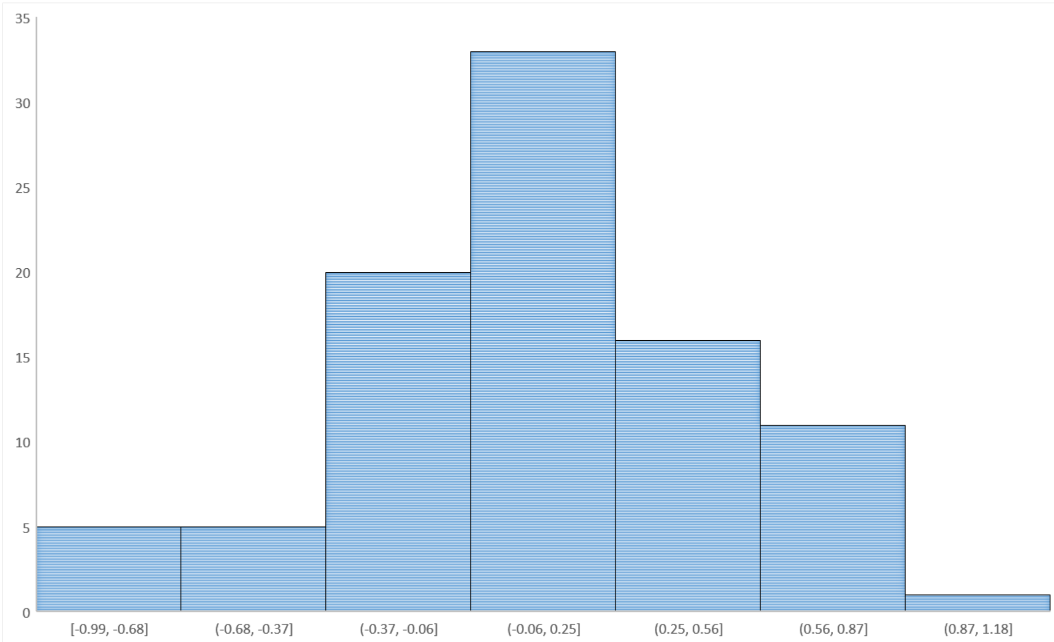

Figure 4
Histogram of shock pairwise correlations (excluding financial institutions)

5.2 Narrative approach

We use a narrative approach to explicitly link our firm-level shocks to actual idiosyncratic firm-level events. This is a relevant exercise given our imperfect measure of firm-level shocks. Among the most important firm-level events, we find successful launches of new brands/models, accessing new markets, weak market demand, strikes, regulatory problems/notices and changes in CEO. Different managerial skills of a new CEO or regulatory issues that prevent a company from implementing a new plan are good examples of changes in companies' productivity. Table 5.1 presents a summary of 10 firm-level events, together with the corresponding firm-level shock $(g_{it} - \bar{g}_{it})$ and the sales to GDP ratio (s_{it-1}/GDP_{t-1}).

Let's start describing the events in Table 5.1. In 2003, Rio Tinto experienced weak international demand for commodities, increased operational costs (through increasing oil prices as well as natural/operational disasters) and dollar depreciation (most of its earnings denominated in dollars). Additionally, two important operational issues affected the company's performance: the slippage at the Grasberg mine (Indonesia) impacted production volumes and costs, and a 3-week smelter shut-down at Kennecott Utah Copper as a result of the acid plant failure also affected the company's production. These events are consistent with the evolution of Rio Tinto's shock. In particular, Rio Tinto's demeaned labour productivity in 2004 declined by 87.7%, while the company's turnover as a share of Australian GDP was 1.4%. I now describe the next events in Table 5.1 using a similar approach.

2004: Qantas had recently launched low-cost brand Jetstar Airways–created to compete with low-cost airline Virgin Blue–expanded into Asian markets. The increased demand for Qantas services is associated with a 24% increase in Qantas' demeaned labour productivity.

2005: The Australian Competition and Consumer Commission (ACCC) dropped its competition notice on Telstra and ordered Telstra to reduce its wholesale DSL price over a period of time and to pay $6.5 million in rebates to its wholesale customers. In addition, effective July 2005, a new CEO (Solomon Trujillo) was appointed. Telstra's demeaned labour productivity growth fell by 21%.

2006: Due to regulatory problems, Telstra had to abandon a project to build a high-speed fibre-optic network in Australia. There was disagreement over how much the company could charge its competitors to access the network. Also, Telstra had to engage resources in removing most public phones owned by the company because of vandalism and the shift to mobile telephones. Telstra's demeaned labour productivity growth fell by 8%.

2011: Lendlease started a series of structural changes to focus their operations in more profitable projects. The company retired five of its existing brands and entered the health business. Lendlease's demeaned labour productivity declined by 57% in 2011. In addition, the company suffered from the 2011 Queensland floods.

2011: Qantas faced long-lasting industrial negotiations with three unions: the Australian Licensed Aircraft Engineers Association (ALAEA), the Australian and International Pilots Association (AIPA) and the Transport Workers Union (TWU) of Australia. Failed negotiations resulted in the grounding of all Qantas aircraft and a lockout of the airline's staff for 2 days. Fair Work Australia ordered that all industrial action taken by Qantas and the involved trade unions be terminated immediately, fearing that an extended period of grounding would involve significant damage to the national economy. Qantas's demeaned labour productivity growth fell by 10.4%.

2012: Lendlease expanded into the luxury home market in southern California. The company constructed the Olympic Village for the 2012 Olympic Games in London. Lendlease's demeaned labour productivity increased by 26.4%.

2013: Rio Tinto, with the goal of focusing on its larger and more profitable operations, sold majority stakes in its coal mines. These operations led to an increase of 18.1% in demeaned labour productivity.

2015: Telstra announced that CEO David Thodey would retire and be replaced by Andy Penn (in May 2015). The new CEO strategy experienced a setback with the failure of a joint venture to build a mobile phone network in the Philippines. Telstra's demeaned labour productivity declined by 8%.

2015: Rio Tinto experienced poor management of its African iron business, which led to issues with the Guinean government. The company also suffered from the large decline in commodity prices. Rio Tinto's labour productivity declined by 11%.

Overall, the analysis of shocks' pairwise correlations and the narrative approach indicate that the predictive power of the granular residual is more likely due to idiosyncratic firm-level events driving aggregate GDP, rather than the reverse.

Table 5.1

Narrative approach

Year	Company	$g_{it} - \bar{g}_{it}$	$\frac{s_{it-1}}{GDP_{t-1}}$	Event
2003	Rio Tinto	-87.7%	1.4%	Weak market demand; natural/operational disasters
2004	Qantas	+23.2%	1.3%	Expansion to Asian markets with recently founded Jetstart
2005	Telstra	-21%	2.5%	ACCC sanctions and new CEO
2006	Telstra	-8.7%	2.2%	Regulatory problems, new projects and removal of public phones
2011	Qantas	-10.4%	1.3%	Dispute with the TWU
2011	Lendlease	-57.4%	1.0%	Wide changes to groups of brands; Queensland flood
2012	Lendlease	+26.4%	1.0%	Enter mansions market; Olympic village
2013	Rio Tinto	+18.1%	5.1%	Sold majority stakes in coal mine to focus on large operations
2015	Telstra	-7.9%	1.8%	New CEO; failed joint venture to build network in the Philippines
2015	Rio Tinto	-11.7%	4.2%	Poor management in iron business; Decline in commodity prices

6 Conclusion

We explored the hypothesis of the granular origins of business cycle fluctuations for the Australian economy. We first showed that the distribution of firm size in Australia follows a power law, with few firms being disproportionally large. We then measured firm-level productivity shocks and documented that shocks to a small number of large non-financial firms accounted for a large share (20%-40%) of the fluctuations in Australian GDP growth for the period 2000–2018. Besides confirming the importance of energy sector firms (such as Rio Tinto), we documented that shocks to large firms in the transportation, construction and consumer service sectors (including Qantas, Telstra and Lendlease) also appear to be important drivers of GDP growth.

We performed two robustness check exercises to validate the granular view of the Australian economy. First, we examined the pairwise correlations between our firm-level shocks. A high correlation between firm-level shocks would indicate that an aggregate shock drives GDP and firm-level performance. We instead showed that the pairwise correlations of non-financial firms are distributed around zero, indicating that our shocks have an important idiosyncratic component. Second, we used a narrative approach and linked firm-specific historical events to our measured shocks. Both exercises supported the view that idiosyncratic firm-level shocks are an important source of business cycle fluctuations.

Our findings highlight the importance of modelling the Australian macroeconomy from a disaggregated perspective by considering the role of firm-level heterogeneity and idiosyncratic firm-level shocks. Our results have important consequences for policy-making. By studying and monitoring the behaviour of the top non-financial Australian firms, policymakers can gain substantial predictive power about future economic activity, as well as about preventing and/or mitigating episodes of sharp and prolonged declines in economic growth.

While we see our findings as a contribution to gain a better understanding of the sources of business cycles in Australia, we believe that there are several avenues for future research. First and foremost, it would be important to gain access to better data on Australian firms in terms of frequency, the variables available, the number of firms with non-missing data and the time span. In this sense, access to the BLADE database for academics would be an important step forward.[17] Another important avenue for future research would be to consider explicitly the role of market power, concentration and price mark-ups from a granular perspective.

[17] http://www.abs.gov.au/websitedbs/D3310114.nsf/home/Statistical+Data+Integration+-+Business+Longitudinal+Analysis+Data+Environment+(BLADE)

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Appendix

Table 6.1
Revenue and employee summary statistics, 2016, Missing values

Variables	Num. firms	bottom25	bottom50	top50	top75	top95
Revenue	1,198	300	599	599	301	50
Employee	103	8	23	80	55	19
Ratio row 2/raw 1	8.6%	2.6%	3.8%	13.4%	18.3%	31.7%

Note: The data is sourced from S&P Global Market Intelligence. The unit for revenue is millions of U.S. dollars.

Table 6.2
Descriptive statistics annual data: 1999-2017

Variable	Obs	Mean	Std. Dev.	Min	Max
Real GDP growth	18	2.94%	0.77%	1.92%	4.0%
Granular residual non-financial firms (% change of residual)	18	-0.15%	1.44%	-4.67%	2.04%
Real Exchange Rate growth	18	2.30%	11.05%	-19.38%	29.41%
Terms of trade growth rate growth	18	2.89%	8.43%	-10.41%	20.44%
Monetary policy shock (percentage points)	18	0.003	0.099	-0.165	0.189
Government spending shock (% change of G)	18	-0.14%	0.61%	-1.41%	0.84%
Uncertainty shock (% change of index)	18	-0.35%	9.14%	-21.34%	19.83%

We proceed to study the effect of the granular residual of the top-200 firms in Australia.

Top-200

Table 6.3
Granularity in Australia (Top-200)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	RGDP	RGDP	RGDP	pcGDP	pcGDP	pcGDP
$\hat{\Gamma}_t$	0.39***			0.46**		
	(0.127)			(0.165)		
$\hat{\Gamma}_t^E$		0.35***			0.45***	
		(0.112)			(0.147)	
$\hat{\Gamma}_t^{noF}$			0.41***			0.48**
			(0.128)			(0.168)
Observations	17	17	17	17	17	17
R-squared	0.237	0.184	0.245	0.228	0.204	0.236

* Note: This table presents the OLS coefficients of regressing GDP growth against the top-200 granular residual and its own lag. In columns 1 to 3, the dependent variable is real GDP growth, while in columns 4 to 6 the dependent variable is per-capita GDP growth. $\hat{\Gamma}_t$ is the granular residual with all top firms. $\hat{\Gamma}_t^E$ contains only Energy sector firms, while $\hat{\Gamma}_t^{noF}$ excludes financial institutions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sales growth

Table 6.4
Granularity in Australia (Sales Growth, Top-100)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	RGDP	RGDP	RGDP	pcGDP	pcGDP	pcGDP
$\hat{\Gamma}_t^s$	0.42**			0.47**		
	(0.147)			(0.187)		
$\hat{\Gamma}_t^{s,E}$		0.42**			0.44*	
		(0.154)			(0.208)	
$\hat{\Gamma}_t^{s,noF}$			0.44***			0.49***
			(0.116)			(0.154)
Observations	17	17	17	17	17	17
R-squared	0.292	0.282	0.327	0.234	0.215	0.272

[*] Note: This table presents the OLS coefficients from regressing GDP growth against the top-100 granular residual (with sales growth) and its own lag. In columns 1 to 3, the dependent variable is real GDP growth, while in columns 4 to 6, the dependent variable is per capita GDP growth. $\hat{\Gamma}_t$ is the granular residual with all of the largest firms. $\hat{\Gamma}_t^E$ only contains energy sector firms, while $\hat{\Gamma}_t^{noF}$ excludes financial institutions. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1