RESEARCH PAPER 7/2019

Do manufacturing entrepreneurs in Australia have (or develop) a productivity advantage?

Sasan Bakhtiari

July 2019

Abstract

Young firms are integral to productivity enhancing resources reallocation. However, they need to be more productive than the average firm to play that part. In Australia, manufacturing entrepreneurs are quite unproductive upon entry. Yet, the productivity of those that survive makes a quantum leap in one year and starts to converge to that of the mature firms. Those entrepreneurs that grow substantially by age three, termed as transformative, have a major productivity advantage. Interesting productivity dynamics are also afoot for entrepreneurs located within clusters of firms and patents that lead to productivity advantages. The findings shed light on a multitude of externalities affecting the productivity of young firms and have implications for the related government policies.

JEL Codes: D24, L26, L6, M13, R12

Keywords: Entrepreneurship, Survival, Productivity, Growth, Clusters, Patents

Australian Government
Department of Industry, Innovation and Science
Office of the Chief Economist

For further information on this research paper please contact:

Sasan Bakhtiari

Industry and Firm Analysis

Department of Industry, Innovation and Science

GPO Box 9839

Canberra ACT 2601

Phone : +61 2 9397 1639

Email: sasan.bakhtiari@industry.gov.au

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Key points

- **Young firms in Australia are quite unproductive upon entry.**
- **Surviving ones improve their productivity and become as productive as incumbent firms.**
- **A small number of entrepreneurs are very productive and grow very fast (dubbed transformative).**
- **Entrepreneurs that start within clusters of patents and firms have much faster productivity growth than other firms.**
- **Co-locating with suppliers and clients does not seem to provide firms with much incentive to improve their productivity.**

1. Introduction

It is well established that aggregate productivity growth is partly driven by the reallocation of resources from less productive to more productive units in the economy (see Baily et al., 1992; Olley & Pakes, 1996; Foster, Haltiwanger, & Krizan, 1998, 2006, for instance). Young firms are an integral part of this productivity enhancing resources reallocation by challenging and transforming the status quo. The incumbent firms that are unable to react and adapt to the constantly changing environment will fail and their resources will be taken over by the younger firms. The more productive these young firms are, the larger the magnitude of productivity gains from the reallocation process.

Australia, in its own right, enjoys a level of entrepreneurship comparable to many other industrial countries (Bakhtiari, 2017). However, a high level of entrepreneurship, per se, does not imply productivity growth. Many entrepreneurs are under-performers and exit. Those that survive can only contribute to productivity growth if they have some productivity advantage over other firms. With this in mind, I explore whether surviving entrepreneurs in Australia exhibit some productivity advantage over other firms. If this is not the case, then the question turns into which classes of entrepreneurs are the impetus for productivity growth?

The initial findings show that an average entrepreneur is quite unproductive upon entry, with productivity measured as Total Factor Productivity (TFP). However, the productivity level of entrepreneurs that survive the first year makes a remarkable leap as they establish themselves and realise their potential. Still, the productivity of the surviving entrepreneurs over time gets just as good as that of the more mature firms.

Delving deeper, I find that certain groups of entrepreneurs do exhibit substantial productivity advantage or develop one over time. Transformative entrepreneurs – those with considerable growth by the age of three – are the most productive ones. However, as one would expect, their number is very small.

There are also entrepreneurs that co-locate with firms of the same industry or start within high-patenting areas. These firms do not have a productivity advantage upfront but develop one. A more intensive selection process that only allows the more productive firms to survive together with a higher rate of productivity growth gradually give the surviving entrepreneurs in these clusters an edge over other firms. I also look at the effect of co-location with clients and suppliers and find interesting dynamics but of weaker consequences.

The remainder of the paper is organised as follows: the next section describes the data. Entrepreneurship is defined in Section 3. In Section 4 I explain the computation of productivity and present the preliminary findings. Other key variables used in the modelling are introduced in Section 5. Findings pertaining to productivity advantages and productivity dynamics come in Sections 6 and 7. In Section 8, I conduct a few robustness tests. Finally, the paper is concluded in Section 9.

2. Data

The source of firm-level data used for this study is the Business Longitudinal Analysis Data Environment (BLADE) from the Australian Bureau of Statistics (ABS). The core body of these data integrates the Business Income Tax (BIT) data, Business Activity Statement (BAS), and Pay-As-You-Go (PAYG) data.1 The coverage of the data is all firms that are registered for Goods and Services Tax (GST) at some point in time. The data currently runs from fiscal year 2002 to 2015.2 The full scope of the data provides data on about two to three million active firms a year, of which about 70,000 belong to the manufacturing division.

The information provided in the core body of the BLADE include firms' Australia and New Zealand Standard Industry Classification (ANZSIC), income items, expenditure items, wages, headcount employment, and a series of other operational and financial information that firms are obligated to report to the Australian Taxation Office. The ABS estimates the Full-Time equivalent Employment (FTE) using a combination of wages reported in PAYG and BAS and ancillary data sources and adds it to the BLADE. At the time of this project, employment data is not available for fiscal year 2015.

The main firm identifier on the data is the Type of Activity Unit (TAU). By the ABS definition, a TAU is "a producing unit comprising one or more legal entities, sub-entities or branches of a legal entity that can report productive and employment activities via a minimum set of data items" (ABS Cat.No.1292.0). TAUs can be a stand alone firm or a firm belonging to a larger conglomerate or GST group. TAUs are consistent over time and in the industry that they represent.3

In this work, I restrict myself to Manufacturing (ANZSIC 11xx–25xx) for the main reason that the computation of productivity within this group is a standard practice. This restriction also allows me to keep the size of the sample within practical limits for the computational power available to me.

Employment reports are essential for the estimation of productivity, and I notice that many firms in the BLADE are not reporting their employment. A large number of these firms are non-employers and do not have to report. Where the firm reports zero wages, I set FTE to zero. Still, a number of firms reporting non-zero wages have missing employment. I impute employment for these latter firms as follows: when I estimate a linear regression of log of FTE on the log of wages, and industry and year dummies, I get an R^2 of 0.895 for the fit. Given that the fit is a very good one, I use the estimated model to impute the FTE where it is missing and wages are reported knowing that the imputation noise is going to be small.

[1] See ABS Cat.No.8171.0 for full details about the data and its integration process.

[2] Fiscal years in Australia are from 1st of July to the 30th June next year. For brevity, I will refer to each fiscal year by the ending year when the tax information are reported.

[3] In the interest of confidentiality, the ABS further masks TAUs in the version of the BLADE available for research and provides a duplicate identifier that has a one-to-one correspondences with the TAUs.

3. Measuring entrepreneurship

Detecting and measuring entrepreneurship in administrative data has certain challenges. The main obstacle is the lack of an explicit indication of entrepreneurship. Most studies in this area proxy entrepreneurship with the start of a business.

The BLADE is an administrative data formed from tax reports, hence, I follow suit and use the first ever appearance of a firm – excluding year 2002 which is the first year – as an entrepreneur entering. In the same vein, I consider the last ever appearance of a firm in the data – excluding the year 2015 which is the last year – as the firm exiting. The emphasis on the first ever and last ever is required as data for some firms has time gaps. These temporary disappearances can be caused by the firm being inoperative during those years. In some cases, the data are simply missing. I avoid counting these *re-entries* as new entrepreneurs.

At this stage, still not every entry is entrepreneurship. I apply one more filter to make entries more correlated with entrepreneurship. If an entry is identified as part of a larger firm or tax group, I do not consider it as an entrepreneur. These new firms are either the new establishment of an already existing firm or a case of acquisition/merger. The two types cannot be distinguished. These cases constitute only about 0.17 per cent of the data and will have a negligible statistical effect on most results. The absence of acquisitions and mergers from entries also means that in the remainder exits are mainly a sign of business failure.

There are also uncertain cases. A new firm can appear for reasons other than entrepreneurship. For instance, new entries can be formed with the establishment of *phoenix* companies,[4] and a change or split in ownership. Given the information in the BLADE, it is impossible to detect and drop these spurious entries. One possibility is when a new firm has more than a hundred employees at the end of their first year. These firms could be spurious entries but also fast growing entrepreneurs.[5] There are only a handful of these firms in the data, and their statistical impact on the findings is negligible.

Lastly, I need to make a distinction between mature and young firms for comparisons. I assign a firm aged three or younger as *young*; firms older than three years of age and firms pre-existing the first year of data are *mature*. Note that a firm is age zero in the year of entry. This classification follows from Bakhtiari (2017) where he finds that by age three job creation and destruction

[4] By Australian Securities and Investments Commission’s description an “illegal phoenix activity involves the intentional transfer of assets from an indebted company to a new company to avoid paying creditors, tax or employee entitlements.” More details can be found at http://www.asic.gov.au.

[5] Note that employment numbers are collected at the end of the fiscal year, not at the beginning.

dynamics among young firms in Australia converges to that of the mature firms.[6]

4. Productivity of manufacturing firms

4.1 Measurement

I estimate the TFP of individual manufacturing firms using a Cobb-Douglas production function, which in log form can be written as

$$y_{jit} = \alpha_i^{(l)} l_{jit} + \alpha_i^{(k)} k_{jit} + \omega_{jit} + \epsilon_{jit}, \tag{1}$$

where y is the log of value added output, and l and k are the logs of labor and capital, respectively. ω is the log of productivity for firm j belonging to industry i at time t. ϵ is a zero mean and random noise component.

Olley & Pakes (1996) show that using Ordinary Least Squares (OLS) to estimate the coefficients in (**Error! Reference source not found.**) could lead to biased estimates, since firms can respond quickly to productivity shocks by adjusting labour. De Loecker & Warzynski (2012) propose a two-stage method to overcome this endogeneity problem. The first stage involves a non-parametric estimation of the following:

$$y_{jit} = \Phi(l_{jit}, k_{jit}, m_{jit}, z_{jit}) + \epsilon_{jit}, \tag{2}$$

where *m* is the material input and *z* is a set of instruments. For this application, *z*={*Export*,*Foreign*}, where *Export* dummy means that a firm has non-zero income from exports and *Foreign* dummy means that a firm has more than 50 per cent foreign ownership. I then carry out an OLS estimation by setting $\Phi(.,.,.)$ to a translog function of order three interacted with both *Export* and *Foreign* dummies.

Now, let's assume that productivity dynamics has the following Markov property

$$\omega_{ji,t+1} = g_t(\omega_{jit}, Export_{jit}, Foreign_{jit}) + \xi_{jit}. \tag{3}$$

Using

$$\begin{aligned} \omega_{ji,t}(\alpha) &= \widehat{\Phi}_{jit} - \alpha_i^{(l)} l_{jit} - \alpha_i^{(k)} k_{jit}, \\ g(\omega) &= a_0 + a_1\omega + a_2\omega^2 + a_3\omega^3 + a_4 Export + a_5 Foreign, \end{aligned} \tag{4}$$

one can compute $\xi_{jit}(\alpha)$ for a given value of α, where $\widehat{\Phi}$ is the predicted value from stage one. The moments to satisfy for the estimation of α's are (De Loecker & Warzynski, 2012)

$$\xi_{jit}(\alpha) \perp \{1, l_{ji,t-1}, k_{jit}\}. \tag{5}$$

Since labor is expected to be correlated with productivity shocks, lagged values of labor are used in the moments as instruments.

[6] There are other definitions of young firms. For instance, the OECD defines young firms as five years old or younger. The definition used here is reflective of the dynamics that take place specifically in Australia that are different to those in Europe and the US.

For the estimation of TFP, the value added output is computed as turnover minus the cost of purchases and contracting out adjusted for change in inventories. The subtraction of contracting out costs addresses concerns by Houseman (2007) that not doing so could result in the over-estimation of productivity for firms that are contracting out.

Labour is one plus FTE, noting that the owner or founder is also contributing to the firm. This consideration is essential so that non-employing firms, which are about 37 per cent of the data and a larger proportion of entrepreneurs, are included. Material costs are the reported purchases and other costs.

Capital is constructed using a perpetual inventory model of the form

$$K_{jit} = (1-\delta)K_{ji,t-1} + I_{t-1} + \frac{LS_{jit}}{\delta+g}, \tag{6}$$

where the depreciation rate of capital is set to $\delta = 0.05$ accounting for an average lifetime of 20 years. LS is the leasing stock of capital. Following Breunig & Wong (2008), I set the rate of capital growth to $g = 0.08$. For the initial capital stock, I use the report of non-current assets. Investment, I, is measured by the reported capital expenditures. In case non-current asset is missing in the first year, I use $I/(\delta+g)$ as the estimate of the initial capital.

All monetary values are deflated using appropriate indexes. Turnover is deflated using manufacturing output price indexes (ABS.Cat.No.6427.0.12). Material cost is deflated by the manufacturing input price indexes (ABS Cat.No.6427.0.14). Capital expenditure and leasing stock are deflated using the output price index of machinery and equipment manufacturing (ANZSIC 24). This choice is justified by the fact that most of the capital to manufacturing is supplied by this particular sector.

The coefficients in are estimated separately for two-digit ANZSICs. The estimated values are listed in the appendix Table A.

Part of the variation in the estimated TFPs are still driven by the difference in individual markups. De Loecker & Warzynski (2012) also suggest a way of correcting for these markups. To apply the correction, they assume that labour is the variable input and use the inverse of wages in the computation of markups. As mentioned earlier, the existence of large number of non-employers is an impediment to the application of this correction. Dropping non-employers, on the other hand, introduces substantial bias in the estimates and hinders observing entrepreneurs particularly in their first year. In view of this issue, I proceed with revenue TFP. On positive side, Foster et al. (2008) show a very strong correlation between physical and revenue measures of productivity in practice. Accordingly, omitting the markup correction has only very minor effect on the results.

TFP can be computed for only a subset of firms that fully report their labour and capital. Several firms missing labour or capital seem to be operational. I apply an inverse propensity weight (w) to each observation with available TFP to reduce the missing data bias. To do this, I first estimate a Probit model where the dependent variable is a dummy that indicates whether TFP is available or missing for an observation. The independent variables are the log of turnover, whether the firm is young, and industry and year dummies. I then use the estimated model to predict the propensities and use their inverse as weights.

Finally, since TFP is unitless, I scale it so that the median of TFP (using inverse propensity weights) is equal to one.

Table 4.1 shows the number of manufacturing firms in the data in each year. The first two numbers for each year are the actual counts. On average, there are close to 70,000 manufacturing firms per year, of which an average of 14,500 firms are young (three years of age or younger).

Table 4.1 Simple and weighted count of firms.

			TFP Available			
			Count		Sum of Weights	
Year	All	Young	All	Young	All	Young
2003	71,146	5,440	27,287	1,252	67,628	5,547
2004	72,237	11,501	26,346	2,856	70,159	11,656
2005	73,318	16,755	31,927	5,333	69,494	15,705
2006	73,538	20,958	30,956	6,705	73,310	22,719
2007	73,083	20,128	29,356	6,335	70,679	19,825
2008	71,731	18,473	23,244	4,569	72,798	19,864
2009	69,168	16,104	26,577	4,860	66,868	15,996
2010	68,435	15,217	27,622	4,734	71,910	20,136
2011	67,349	13,824	26,700	4,205	65,503	13,531
2012	66,075	12,921	26,158	3,954	64,653	12,873
2013	64,075	12,155	25,722	3,772	63,140	12,331
2014	62,620	11,570	22,912	3,241	62,827	11,395
Total	832,775	175,046	324,807	51,816	754,316	181,578

Source: Department of Industry, Innovation and Science (2018)

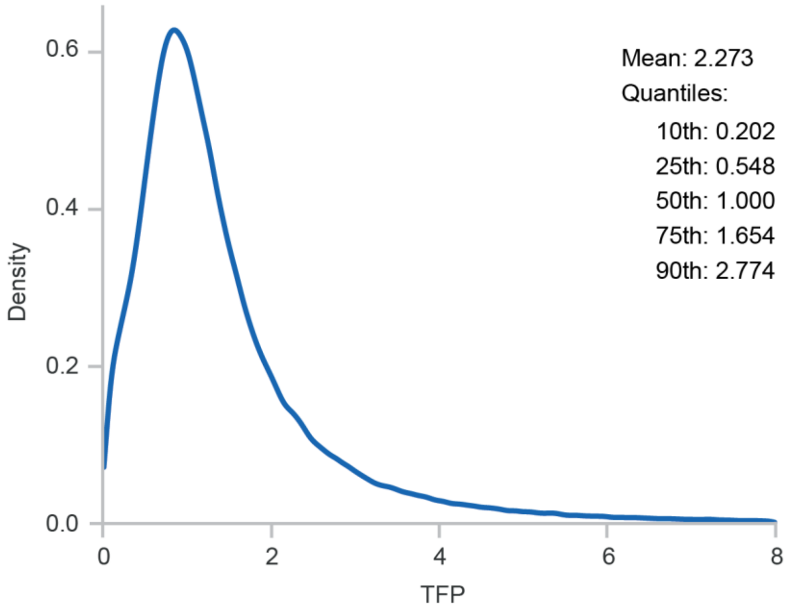
The next two numbers for each year are the number of firms for which productivity can be computed. The numbers show that productivity can be computed for only about 40 per cent of firms in the data. The percentage of young firms for which productivity can be computed is even smaller and is around 30 per cent.

As a reliability check, I am reporting the sum of inverse propensity weights for firms with known productivity in the last two columns. The sum of weights closely mimic the total numbers reported in the first columns in most years.

4.2 Distribution

The distribution of the TFPs is computed using a kernel density estimate and shown in Figure 4.1. The figure shows a relatively dispersed distribution with a falling upper tail. The mean value of productivity is about 2.3 which is close to the 90th percentile. It is likely that the mean value is affected by a few outliers with productivity levels in excess of 3.0. Still, for the majority of observations in the data the productivity is close to one (the median). The interquartile range shows an order of three to one between the productivity of the top and bottom quartiles.

Figure 4.1 The kernel density estimate of the TFP distribution.



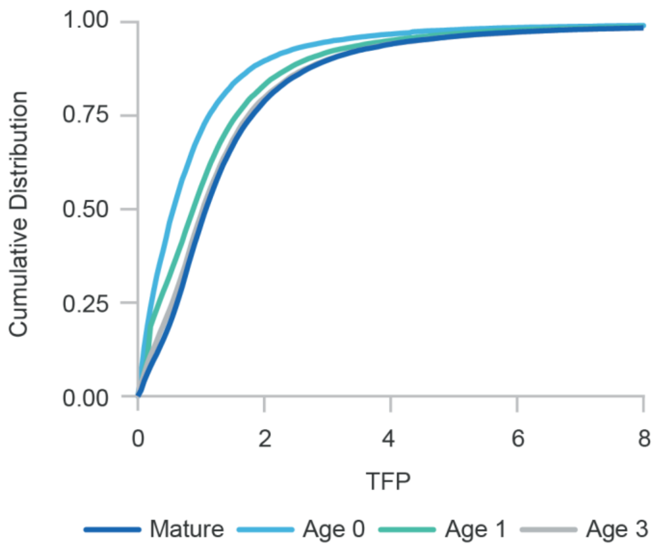
Notes: The inverse propensity weights and a Gaussian kernel are used for estimation.

Source: Department of Industry, Innovation and Science (2018)

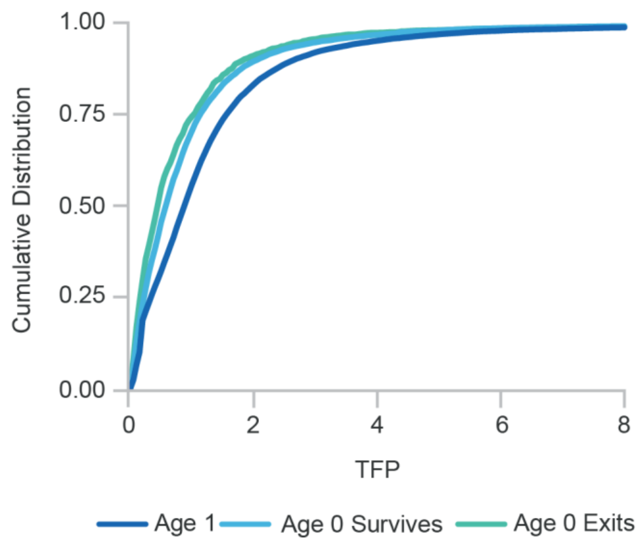
I further compare the productivity distribution of young firms to that of the mature firms for any sign of productivity advantage. For this purpose, I separately compute the empirical Cumulative Distribution Function (CDF) of productivity for young and mature firms. An ordering between the two distributions can be established if one CDF stochastically dominates the other one. To account for possible productivity dynamics that are taking place in the early ages, I further break the population of young firms by age and compute a separate CDF for young firms of each age. The CDFs and the implied dynamics are illustrated in Figure 4.2.

Figure 4.2 The CDF for the TFP of different groups of firms.

(a)



(b)



Notes: The inverse propensity weights are used in estimation.

Source: Department of Industry, Innovation and Science (2018)

Panel (a) illustrates the CDFs for young firms at ages zero (year of entry), one and three against that of the mature firms. The CDFs exhibit an order of stochastic dominance. The least productive firms are those at age zero; their productivity distribution is being stochastically dominated by all other distributions.

Firms that survive into age one are more productive than firms at age zero; their productivity distribution stochastically dominates that of the firms at age zero. The gap between the productivity distributions of ages zero and one especially implies a substantial improvement in the course of the year.

Firms that survive to age three have further productivity advantage over firms at age one; their productivity distribution stochastically dominates that of the firms at age one. In turn, these firms are by far more productive than firms at age zero. However, the gap between the CDFs at ages one and three is smaller than that from ages zero to one; hence, productivity is improving but the gains are slowing down.

Finally, the productivity distribution of mature firms stochastically dominates those of young firms ages zero and one. By age three, the productivity distribution of young firms has mostly converged to that of the mature firms, and the two distributions start to look identical. It appears that young firms in Australia are at best as productive as mature firms and do not have any noticeable productivity advantage over them.

It is important to note that the productivity leap from age zero to one observed in panel (a) is mostly driven by a jump in the productivity of surviving firms and has much less to do with the exit of low productivity firms. To prove this point, in Figure 4.2(b) I illustrate the productivity CDF of exiting firms and surviving firms at age zero. The order of stochastic dominance clarifies that at age zero, exiting firms are less productive than similar firms that survive into age one, therefore, there is some self-selection going on in the conventional sense. However, the margin is very small.

On the other hand, there is a very large gap between the productivity CDF of surviving firms at ages zero and one. The difference indicates that the productivity of individual firms that survive into age one improves substantially from age zero to one. This productivity improvement, and not the exits, counts for most of the first year productivity gain observed in panel (a).

In summary, most entrepreneurs in Australia are quite unproductive upon entry not because they are under-performers, but because they have not established themselves and realised their potentials. Those entrepreneurs that survive the first year are the ones that succeed in establishing themselves and claiming their share of the market. Thus, when talking about the productivity of entering firms, it is more realistic to consider their productivity at age one and after. Productivity levels at age zero can be misleading as they under-represent the firm’s true potentials.

5. Taxonomy of entrepreneurs

The evidence that the surviving entrepreneurs in Australia can only get as good as mature firms goes against the common wisdom that once the selection takes effect the remaining entrepreneurs are productive enough to facilitate resources reallocation. The discrepancy warrants further scrutiny. Is the burden of productivity-enhancing resources reallocation borne by certain group or groups of entrepreneurs? I explore this possibility by introducing a series of classifications generally believed to be associated with superior performance and high productivity. Using these classifications, I embark on establishing a taxonomy of young and mature firms with productivities above (or below) the average.

5.1 Transformative entrepreneurs

Schoar (2010) initially introduced the concept of transformative versus subsistence entrepreneurs, where transformative entrepreneurs tend to grow fast, create many jobs and transform markets. Subsistence entrepreneurs, on the other hand, tend to stay small and generate subsistence income for the owner and possibly for a few other employees. In most economies, there is an emphasis on transformative entrepreneurs as they are the agents of innovation, job creation, and productivity growth.

This emphasis extends to Australia, where job creation is an important tenet of current government policy. Transformative entrepreneurs are also a natural place to look for productivity advantage. The investigation, however, is hampered by a lack of consensus about what exactly constitutes being transformative.

I define transformative entrepreneurship based on fuzzy logic. Fuzzy logic concerns the modelling of concepts and decisions that rely on subjective, rather than on objective, descriptions (Zadeh, 1965). In this sense, transformative entrepreneurship is a good candidate. Specifically, I base my definition of transformative entrepreneurs on the following two subjective rules:

Rule 1: has shown substantial growth in turnover by age three; and
Rule 2: has created a number of jobs by the same age.

The rules take into account two facts. First, new firms in Australia start to behave very similar to mature firms by the age of three (Bakhtiari, 2017). Therefore, any entrepreneur not showing fast growth upfront is unlikely to show fast growth later.

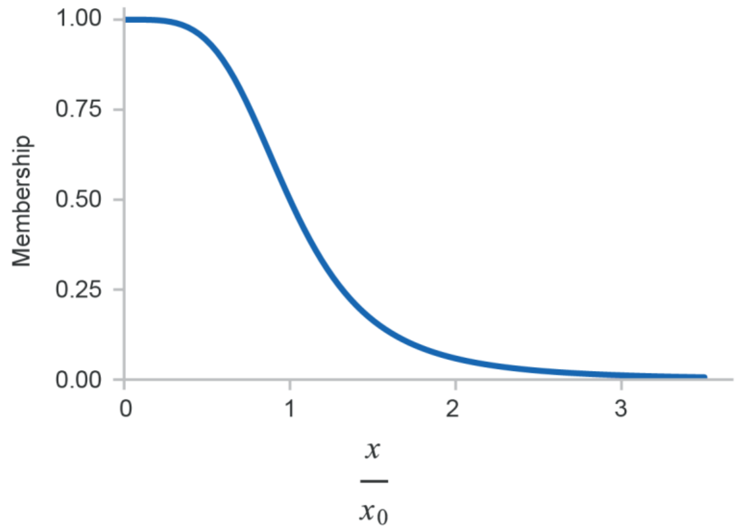
Second, with the advent of internet and an increase in job automation, firms are becoming less and less reliant on hiring labour to expand. For that reason, Rule 2 only requires some job creation alongside turnover growth and not job creation at the same rate as turnover growth.

To apply the rules, I first define the following membership function:

$$\mu(x; x_0, \kappa) = \frac{1}{1+(x/x_0)^{\kappa}}. \tag{7}$$

In this function, $\mu \in [0,1]$ indicates the degree to which x is a small number, and $1-\mu$ is the degree to which x is large. At x_0, a number is equally small and large. Parameter κ depicts the level of subjectivity in the classification, with higher values of κ showing lower levels of subjectivity. $\kappa \to \infty$ is the conventional dummy variable. Figure 5.1 shows a fuzzy membership function with $\kappa = 4$, which will be used throughout this paper. In this classification, number $x = 3x_0$ is large and number $x = 2x_0$ is ‘somewhat’ large.

Figure 5.1 The fuzzy membership function with κ=4.



Source: Department of Industry, Innovation and Science (2018)

Using this membership function, I classify a transformative entrepreneur as

$$T_{jit} = \min\{1 - \mu(Turnover_{jit}(age = 3); \$10m, 4),$$
$$1 - \mu(FTE_{jit}(age = 3); 10{,}4)\}. \quad (8)$$

The first term in the minimization is the degree to which an entrepreneur demonstrates substantial growth in turnover by age three (Rule 1), given that turnover starts from zero at the very beginning. This formulation follows the ATO's classification that considers firms with less than $10 million annual turnover as small firms. The membership function treats an entrepreneur that has just reached the threshold of $10 million equally transformative and non-transformative. Only entrepreneurs that move well beyond that threshold by the age of three are considered transformative with a good degree of certainty.

The second term in the minimization indicates the degree to which a number of jobs have been created (Rule 2), again, given that employment starts at zero at the very beginning. I am relying on the ABS convention that defines firms with fewer than 20 employees as small. Choosing a threshold of 10 signifies that the firm has created jobs, but its pace of job creation does not have to match its rate of turnover growth.

Taking the minimum of the two membership functions is the fuzzy equivalent of taking the intersection or 'and' between the two rules (Zadeh, 1965). The value of T is constant for an entrepreneurs from age zero to three. For mature firms and entrepreneurs older than three, the value of T is set to zero.

5.2 Industrial clusters

Another place to look for productivity advantage is within industrial clusters, where firms co-locate with other firms of the same industry or with clients or suppliers. A host of economic studies postulates that due to more intense competition and proliferative knowledge spillovers, clusters are environments conducive to innovation and growth (See Ellison et al., 2010; Delgado et al., 2014, for instance). I put this hypothesis to test by computing indexes of clustering separately for co-locating with firms in the same industry (industry clusters), supplying firms (supplier clusters), and client firms (client clusters) .

The definition of industry clustering index is closely based on the M-index of Marcon & Peuch (2010) and is formulated as

$$C_{jit} = \log\left(1 + \frac{T_{jit}/N_{jit}}{T_t/N_t}\right), \tag{9}$$

where

$$T_{jit} = \sum_{\substack{j' \neq j,\ i(j')=i(j) \\ i}} \mu(d_{j,j'}; 5km, 4), \qquad N_{jit} = \sum_{j \neq j'} \mu(d_{j,j'}; 5km, 4) \tag{10}$$

In (10), d is the physical distance between firms j and j' measured by applying the Haversine formula to the geographic coordinates of the two firms. A fuzzy indicator is used to define proximity, where firms at a 5km distance are equally proximate and far. This approach especially reduces the sensitivity of results to the choice of the radius.

N_t and T_t are the total count of firms and count of firms in the same industry as j, respectively. T_{jit} and N_{jit} are the respective counts of firms within the proximity of firm j. Finally, a log transformation is applied to reduce the impact of larger values on the results. For accuracy, I am using all active firms (those with non-zero turnover) for the computation of the indexes and not just the weighted firms.

This clustering index measures the concentration of firms of the same industry around firm j relative to when firms are distributed uniformly. For a totally isolated firm, $C = 0$. The index increases monotonically as the concentration of firms around firm j increases. In a similar fashion, one can define the supplier clustering index as

$$C_{jit}^S = \log\left(1 + \frac{T_{it}^S/N_{it}^S}{T_t/N_t}\right), \tag{11}$$

in which

$$T_{jit}^S = \sum_{j' \neq j} w_{i(j),i(j')}^S \times \mu(d_{j,j'}; 5km, 4), \qquad i(j') \neq i(j). \tag{12}$$

In (12), the weights $w_{i(j),i(j')}^S$ are the share of input sourced by the industry of j from the industry of j'. This approach follows that of Brown & Conrad (1967) and uses input-output shares in the absence of information about who buys from whom. The input shares are computed using the ABS reported input-output tables (ABS.Cat.No.5209.0.055.001). Since the dynamics of input-output tables are very slow and reliable tables are missing prior to 2006, I only use the input-output table for the year 2007. N^S is computed similarly but summing over all firms.

The client clustering index has a similar form and is defined as

$$C_{jit}^{C} = \log\left(1 + \frac{T_{it}^{C}/N_{it}^{C}}{T_t/N_t}\right), \tag{13}$$

in which

$$T_{jit}^{C} = \sum_{j' \neq j} w_{i(j),i(j')}^{C} \times \mu(d_{j,j'}; 5km, 4), \qquad i(j') \neq i(j). \tag{14}$$

The weight $w_{i(j),i(j')}^{C}$ is the share of output sourced form the industry of j by the industry of j'. N^C is computed similarly but summing over all firms.

In the BLADE, the address of firms, hence their exact location, is censured and only the firm's postcode is visible to the researcher. For this reason, I assume that all firms in a postcode are located at its centroid. I then measure the distance between firms as the distance between the centroids. This quantization of addresses introduces some inaccuracy into the measured distances, in particular, where the postcode area is very large. I run a robustness test in Section 8.2 using only smaller postcodes to alleviate concerns on this issue.

The other caveat concerns multi-location firms. In these cases, the postcode is likely the location of headquarter. This issue does not have a significant statistical effect on the results, since 92 per cent of firms in the data are small and single-location. Note that the clustering indexes introduced above only rely on the count of firms and not on their size.

To find the centroid of each postcode, I use the Geocoded National Address File (GNAF) from PSMA Australia Ltd. The GNAF is a publicly available dataset that lists the geo-coordinate of every address in Australia.[7] I find the centroid of a postcode by averaging the geo-coordinates of all addresses listed in that postcode. In this way, the centroid tends to be closer to the denser areas of a postcode where an address is more likely to be found.

5.3 Patent clusters

In addition to industrial clusters, I also look at clusters of patents as another environment fit for productivity enhancement. Patents are a proxy for innovation and cutting edge technology (though an imperfect one). In turn, innovation breeds productivity and growth.

Importantly, patent clusters have little overlap with industry clusters. This distinction is owing to patent clusters representing university campuses and research centres among others. The latter institutions are absent from industry-based clusters that solely represent a concentration of manufacturing firms.

I use Intellectual Property Government Open Data (IPGOD) published by IP Australia to form an index of patent clustering. The data is a publicly available source of information on all patents, trademarks, and design rights issued in Australia.[8]

[7] The GNAF can be downloaded from http://data.gov.au.

[8] The IPGOD can be downloaded from http://data.gov.au.

The data, in particular, provide the geographic coordinates for all Australian patent applicants. I treat the applicants as sources of innovation and knowledge spillover. To crudely adjust for the proportion of patent information held by an applicant, I weight each applicant by the inverse number of applicants for that patent. The weighted total number of applicants in the vicinity of a firm is the basis for the clustering index. Formally,

$$P_{jit} = \log\left(1 + \sum_k \frac{1}{p_k} \mu(d_{j,k}; 5km, 4)\right), \tag{15}$$

where k indexes individual patent applicants, and p_k is the total number of applicants for the patent with applicant k. I am using the same fuzzy indicator of proximity as in the industrial clusters. A log transformation helps to reduce the effect of large values on the results.

5.4 Descriptive statistics

Table 5.1 lists a series of descriptive statistics for young and transformative firms for comparison. By construction, transformative entrepreneurs must achieve reasonable growth by age three. Therefore, statistics are computed for firms of age three, so that proper comparison between transformative and non-transformative entrepreneurs can be made.

Table 5.1 The descriptive statistics for young and transformative entrepreneurs at age three.

	Young	Transformative
Count	33,638	242.6 (0.7%)
Sum of weights	202,358	288.8 (0.1%)
Mean FTE(age=3)	1.1	49.1
Mean Turnover(age=3)	$316,000	$22,902,000

Notes: The inverse propensity weights are used to compute means. Turnover is in 2016 dollars.

Source: Department of Industry, Innovation and Science (2018)

Both the counts and the sum of weights make it clear that transformative entrepreneurs constitute only a tiny fraction of all entrepreneurs, even when restricting the sample to the surviving ones. The average employment and turnover of transformative entrepreneurs, however, distinguishes them from the rest. According to these numbers, an average entrepreneur hires about one full-time employee and earns about $316,000 annually by age three. An average transformative entrepreneur, on the other hand, employs about 49 full-time employees and earns close to $23 million by age three.

Most of the firms detected as being transformative are from relatively high technology industries. Table 5.2 shows that specialised machinery, vehicle and vehicle parts manufacturing, and structural metal products are the industries with the highest number of transformative entrepreneurs. Consequently, the fast growth of this firms is likely accompanied by innovation and the commercialization of novel products.

Table 5.2 Industries with the highest and lowest number of transformative firms.

Panel A: Most transformative

ANZSIC	Description	sum of *T*
231	Motor vehicle and parts	36.7
222	Structural metal products	28.2
246	Specialised machinery and equipment	18.8
161	Printing and the support services	16.8
191	Polymer products	15.0

Panel b: Least transformative

ANZSIC	Description	sum of *T*
189	Other basic chemical products	1.0
118	Sugar and confectionery manufacturing	1.0
170	Petroleum and coal products	1.0
213	Basic non-ferrous metal manufacturing	1.0
134	Knitted products	0.9

Notes: Only firms at age three are used for summation.

Source: Department of Industry, Innovation and Science (2018)

The descriptive statistics for the industry-based clustering indexes and the patenting index are listed separately in Table 5.3. The level of dispersion observed for each index shows that firms in Australia can be located both within highly clustered areas as well as in relative isolation. The median and mean values for each index are very close, suggesting a balance in the number of firms in clusters and outside clusters.

Table 5.3 Descriptive statistics for the key variables.

Statistics	C	C^S	C^C	P
10th Pctl.	0.30	0.48	0.51	0.43
25th Pctl.	0.56	0.61	0.61	1.76
Median	0.74	0.69	0.68	3.45
75th Pctl.	0.92	0.75	0.74	4.55
90th Pctl.	1.19	0.83	0.82	5.19
Mean	0.77	0.68	0.67	3.17
Std.Dev.	0.44	0.18	0.17	1.76

Notes: The inverse propensity weights are used to compute means.

Source: Department of Industry, Innovation and Science (2018)

The correlation coefficient between all the indexes, which will serve as key independent variables in the statistical models, are shown in Table 5.4. There is very little correlation between any two of the indexes. In particular, the weak correlation between the patenting and the industry clustering indexes confirms that the two areas do not have much overlap. The correlation between the patent clustering index and the supplier or client indexes is relatively stronger but far from suggesting a major overlap.

Table 5.4 The table of correlations between key variables.

Variables	*T*	*C*	C^S	C^C
C	0.005			
C^S	0.006	0.020		
C^C	0.002	-0.061	0.362	
P	0.018	0.011	0.260	0.116

Notes: The inverse propensity weights are used.

Source: Department of Industry, Innovation and Science (2018)

Interestingly, the transformative index also has very little correlation with all other indexes. On its face, the weak correlations suggest that the transformative entrepreneurs are a league of their own and do not mingle with firm or patent clusters.

6. Empirical findings

Using the indexes introduced so far, I implement the taxonomy I mentioned earlier using the following linear model:

$$\begin{aligned}\log(TFP_{jit}) = \beta_0 \quad & +(\beta_1^m C_{jit} + \beta_2^m C_{jit}^S + \beta_3^m C_{jit}^C + \beta_4^m P_{jit}) \times Mature_{jit} \\ & +(\beta_1^1 C_{jit} + \beta_2^1 C_{jit}^S + \beta_3^1 C_{jit}^C + \beta_4^1 P_{jit} + \beta_5^1 T_{jit}) \times Age1_{jit} \\ & +(\beta_1^2 C_{jit} + \beta_2^2 C_{jit}^S + \beta_3^2 C_{jit}^C + \beta_4^2 P_{jit} + \beta_5^2 T_{jit}) \times Age2_{jit} \\ & +(\beta_1^3 C_{jit} + \beta_2^3 C_{jit}^S + \beta_3^3 C_{jit}^C + \beta_4^3 P_{jit} + \beta_5^3 T_{jit}) \times Age3_{jit} \\ & +\tau_t + \iota_i + \varepsilon_{jit}\end{aligned} \tag{16}$$

In this model, ε_{jit} is a zero mean and independent noise. β_0 represents the average firm, to which all other groups are compare. $Mature$ and $Age1$ to $Age3$ are dummies signifying firms of different age groups. τ and ι are year and industry dummies, respectively, controling for macro and industry specific effects.

The first line in pertains to the effect an increase in each type of clustering index has on the productivity of mature firms relative to the average firm. The second line models the same effect within young firms of age one. The third and fourth lines, pertain to firms of ages two and three, respectively. Following the earlier discussion, I am dropping age zero firms from the sample as their productivity can distort the results. The estimated coefficients for each index and age group are reported in Table 6.1.

Table 6.1 The effect of key variables on the productivity advantage of mature and young firms of different ages.

Variables	Mature	Age 1	Age 2	Age 3
C	0.098*** (0.005)	-0.027* (0.016)	-0.071*** (0.017)	0.128*** (0.018)
CS	0.040*** (0.012)	-0.264*** (0.044)	-0.259*** (0.045)	-0.200*** (0.050)
CC	-0.092*** (0.013)	0.126*** (0.041)	0.426*** (0.044)	-0.099** (0.048)
P	0.042*** (0.001)	-0.011** (0.004)	-0.067*** (0.005)	0.069*** (0.005)
T	–	1.021*** (0.118)	0.916*** (0.119)	0.294** (0.121)
R2	0.060			
Adjusted R2	0.060			
F	263.04***			
N	305,891			

Notes: Numbers in parentheses are standard errors. *** and ** indicate 1% and 5% significance levels, respectively. Inverse propensity weights are used in the estimation.

Source: Department of Industry, Innovation and Science (2018)

The estimates make it evident that mature firms demonstrate a productivity advantage over the average firm in all types of clusters, except in client clusters. The productivity advantage is especially remarkable with industry and patent clusters.

In Table 6.2 I translate the estimated coefficients in Table 6.1 into percentages of productivity advantage. For continuous indexes, I compare the firm at the 90the percentile of the index to the firm with no clustering.[9]

The results show that firms in an industry cluster whose index is at the 90th percentile (C=1.19) are 12.4 per cent more productive than a firm with no industry clustering. Firms in a patent cluster whose index is at the 90th percentile (P=5.19) are 24.1 per cent more productive than firms with no patent clustering.

[9] The productivity advantage is computed as $100 \times (e^{\beta \times (90th\ percentile)} - 1)$.

Table 6.2 The productivity advantage of different groups of firms in percentages.

Variable	Mature	Age 1	Age 2	Age 3
Industry Clusters	12.3	-3.1	-8.2	16.5
Supplier Clusters	3.4	-19.7	-19.3	-15.3
Client Clusters	-7.2	10.9	41.8	-7.8
Patent Clusters	24.1	-5.5	-29.4	42.8
Transformative	—	177.5	149.9	34.1

Notes: For clusters, 90th percentile is compared to zero. For transformative index, the comparison is between one against zero.

Source: Department of Industry, Innovation and Science (2018)

Among young firms, transformative entrepreneurs demonstrate the most substantial productivity advantage. A fully transformative entrepreneurs ($T = 1$) is 177 per cent more productive than an average firm. However, their productivity advantage erodes by age three as they expand. Very fast growth for transformative entrepreneurs seems to come at the cost of losing some productivity advantage. However, these entrepreneurs can well afford it, beginning far ahead of everyone else in productivity.

The estimates also show that young firms within most clusters start with low productivity levels. With the exception of client clusters, the productivity level of young firms of age one in clusters is below the average which, in turn, means they are much less productive than the incumbents within the clusters.

During the first two years, several dynamics including productivity growth and exit affect the average productivity within each group and move the average in various directions. I will look at the specifics of these dynamics in Section 7.

By age three most young firms are quite settled. As the estimates show, by this age young firms in industry and patent clusters exhibit a productivity advantage not only over the average firm but also over other more mature firms within the clusters. The productivity advantage of young firms at age three over mature firm is statistically significant (Table 6.3). Within client and supplier clusters, on the other hand, young firms do not seem to be developing any productivity advantage.

Table 6.3 *F*-test of whether the coefficients from young firms age 3 are different from those of the mature firms.

Test	Difference	*F* Statistic	p-value
C(Age 3) - C(Mature)	+0.030	7.128	0.008
C^S(Age 3) - C^S(Mature)	-0.240	57.684	0
C^C(Age 3) - C^C(Mature)	-0.007	0.062	0.803
P(Age 3) - P(Mature)	+0.027	69.264	0

Source: Department of Industry, Innovation and Science (2018)

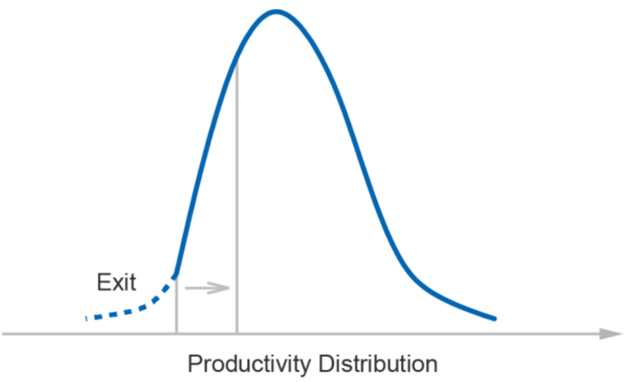
7. Within cluster dynamics

The remarkable increase in the average productivity of young firms within industry and patent clusters is intriguing. It is instructive to understand how these changes are coming about.

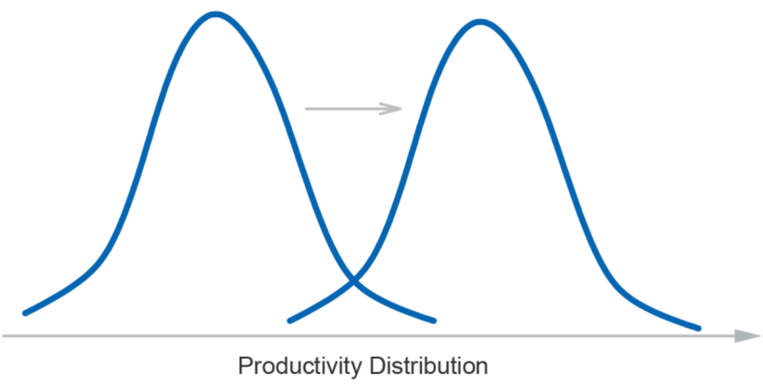
I will consider two mechanisms that can be behind these productivity changes. The first mechanism is the *cutoff effect*. A more intense selection process in clusters would allow only the most productive firms to survive. Some of the exiting firms could have survived elsewhere. The average productivity of surviving firms in the cluster will increase as a result of the productivity distribution being truncated at a higher level (Figure 7.1(a)).

Figure 7.1 Illustration of the two mechanisms leading to an increase in average productivity.

(a) Cutoff effect



(b) Growth effect



Source: Department of Industry, Innovation and Science (2018)

The second mechanism is the *growth effect* which is simply the productivity of individual firms improving over time. The average productivity of the distribution as a whole increases in this way (Figure 7.1(b)).

The higher (or lower) productivity level within clusters can be driven by either or both of the mechanisms mentioned. In the remainder, I look at each of these effects for a better understanding of the underlying productivity dynamics that are taking place in different types of clusters.

7.1 Cutoff effect

As economic theory postulates, cutoff productivity is a productivity level dictated by market and competitive conditions where all firms below that level exit and all firms above it survive.

In practice, it is impossible to observe a clear-cut cutoff productivity level as in the theory. Instead, I compare the productivity distribution of exiting firms in different clusters and determine which distributions are skewed towards higher levels of productivity. Such skewness implies that more productive firms are exiting in those cluster, where they could have survived outside the cluster.

Since the clustering indexes are continuous, I carry out the comparative analysis using a quantile regression of the form:

$$Prob[TFP_{jit} < q] = b_0 + b_1 C_{jit} \quad + b_2 C^S_{jit} + b_3 C^C_{jit} + b_4 P_{jit} + \tau_t + \iota_i, \quad Young_{jit} = 1 \;\&\; Exit_{ji,t+1} = 1. \tag{17}$$

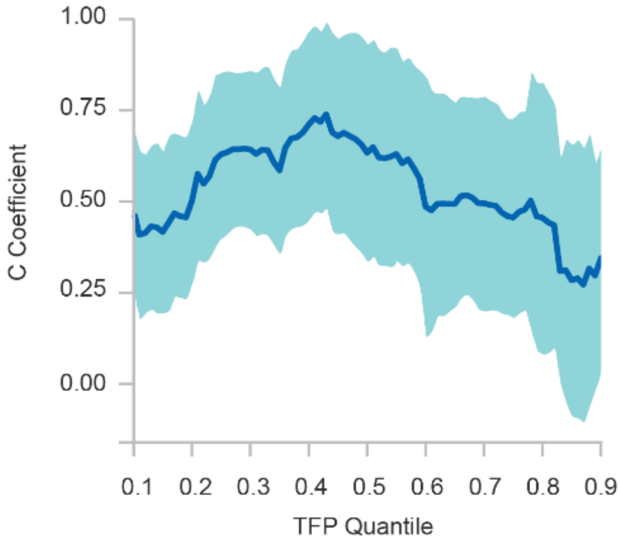
Again, τ_t and ι_i represent time and industry fixed effects. Since, this model is meant to study the productivity distribution of exiting firms, only young firms that are last observed in t, hence exiting in $t+1$, are used for the estimation.

I estimate separately for quantiles ranging from the 10th to 90th percentiles. The estimated coefficients for each clustering index will reveal the direction of the skewness for the productivity distribution of exiting firms in that cluster. The effects for middle to higher percentiles are of special interest as lower productivity firms are expected to exit regardless of their clustering situation.

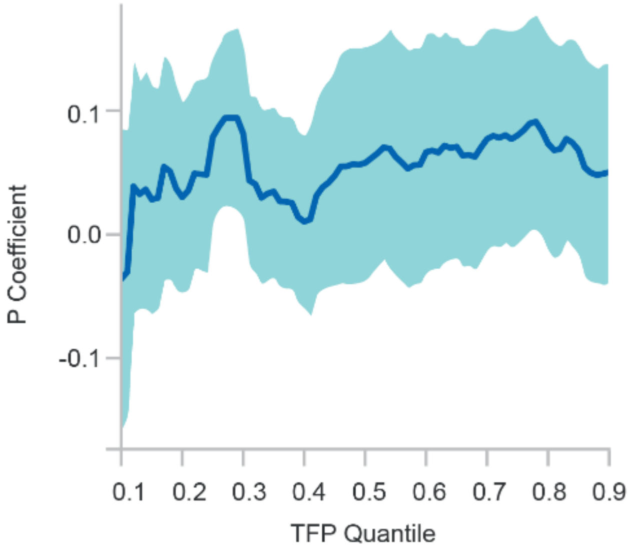
The set of coefficients estimated for each clustering index and for the aforementioned range of quantiles are illustrated in the four panels of Figure 7.2. In each case, the 90 per cent confidence interval is also shown as the shaded area.

Figure 7.2 The quantile effect of different types of clusters.

(a) Industry clusters

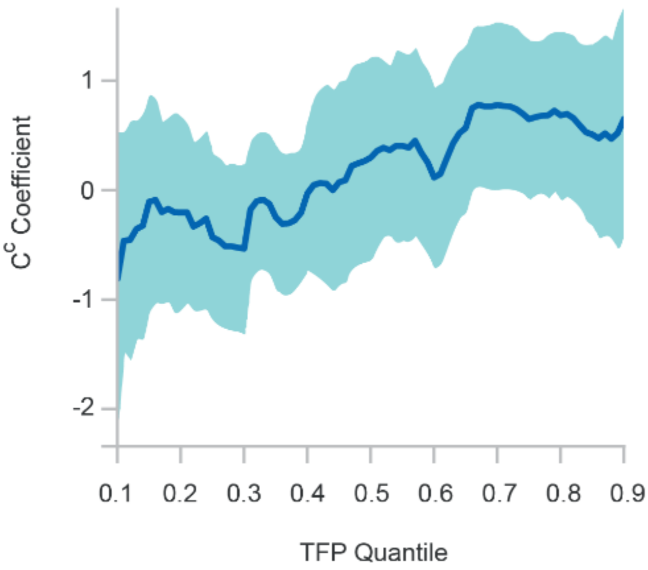


(b) Patent clusters



(c) Supplier clusters

(d) Client clusters



Notes: Shaded area is the 90% confidence interval. Inverse propensity weights are used in the estimations.

Source: Department of Industry, Innovation and Science (2018)

The most notable finding is that of the industry clusters, where firms of the same industry co-locate. As panel (a) of the figure shows, the coefficient is positive for all the quantiles. The coefficients are also statistically significant except for the highest quantiles. In other words, the productivity distribution of exiting firms in industrial clusters is skewed towards higher productivities.

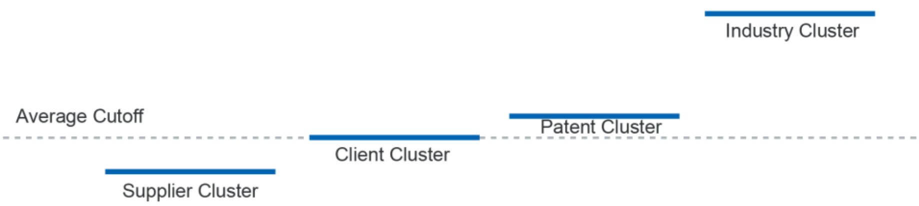
Patent clusters also show some skewness in exit productivity (Panel (b)). However, the estimated coefficients are statistically insignificant except for 20th to 30th percentiles. One can argue that the productivity of exiting firms in patent clusters is higher than the average but only barely.

In contrast, the productivity of firms exiting in supplier clusters is lower than the average. In these clusters, firms that would have failed elsewhere can actually survive. The coefficients estimated for 50th to 80th percentiles are statistically significant.

In the case of client clusters, the estimated coefficients are statistically insignificant for all quantiles. The implication is that the productivity distribution of exiting firms in client clusters is not much different from that of the average firm.

Putting the four pictures together, one can infer an ordering when it comes to some hypothetical cutoff productivity. Clusters of firms from the same industry have the highest cutoff. Patent clusters are next, where their cutoff is slightly higher than the average. Next is clusters with clients, where the cutoff is practically the same as everywhere else. Clusters with suppliers have the lowest cutoff. Figure 7.3 illustrates this ordering.

Figure 7.3 The ordering of hypothetical cutoff productivities by the type of cluster as suggested by the quantile regression results.



Source: Department of Industry, Innovation and Science (2018)

7.2 Growth effect

The cutoff effect concerns the productivity of exiting firms. The growth effect pertains to the productivity of the surviving young firms. In this part, I will focus on firms that survive at least to age three. To look at the productivity dynamics of these firms, I estimate the following linear regression:

$$\log(TFP_{ji,age=3}) - \log(TFP_{ji,age=1}) = \gamma_0 + \gamma_1 \log(TFP_{ji,age=1}) + \gamma_2 \overline{C}_{ji} + \gamma_3 \overline{C}_{ji}^{S} + \gamma_4 \overline{C}_{ji}^{C} + \gamma_5 \overline{P}_{ji} + \gamma_6 T_{ji} + \nu_{ji}. \quad (18)$$

In (18), the change in productivity from age one to three is a function of various firm's characteristics. Clustering indexes are the main objects of interest. I use the value of the index averaged between ages one and three to indicate the average clustering situation over the course of transition. The transformative index is constant over the whole transition. I also average the inverse propensity weights between the two ages before applying them.

The log of TFP at age one is also included as an explanatory variable. Its inclusion reflects the expectation that productivity growth is much slower among firms at or near the production frontier and faster among laggard firms catching up with the frontier. The difference stems from the fact that firms at the frontier need to undertake costly research and innovation to push the frontier. Firms catching up only need to imitate or adopt the already existing technology.

The estimated coefficients for each transition are reported in Table 7.1. As expected, the coefficient estimated for productivity is negative and quite significant both economically and statistically.

Table 7.1 Productivity growth within different groups of young firms that survive to age 3.

Variable	TFP Growth
log(*TFP*)	-0.408*** (0.010)
$\bar{C}$	0.094*** (0.024)
$\bar{C}^S$	-0.003 (0.063)
$\bar{C}^C$	0.107* (0.064)
$\bar{P}$	0.020*** (0.006)
T	-0.109 (0.120)
R^2	0.209
Adjusted R^2	0.203
F Statistic	32.01***
N	7,074

Notes: Numbers in parenthesis are standard errors. *** and * indicate 1% and 10% significances, respectively. Inverse propensity weights average between the two ages are used in the estimation.

Source: Department of Industry, Innovation and Science (2018)

The fastest growth happens within industry clusters. At the 90th percentile of C, productivity grows by nearly 12 per cent from age one to three. The estimated growth is also statistically significant. This evidence supports the observation in Table 6.1 that shows surviving firms showing a substantial productivity advantage by age three.

In the next place are the patent clusters. At the 90th percentile of P, productivity grows by 11 per cent from age one to three. This growth is also statistically significant and is in line with the observations from Table 6.1.

There is also some productivity growth within client clusters. However, the statistical significance is weak. The growth rate among firms in these clusters appear to be rather mixed. Using the estimated coefficient, one finds that productivity grows on average by 9.2 per cent at the 90th percentile of C^C.

Productivity of surviving young firms does not seem to move in any specific direction within supplier clusters. The coefficient in this case is almost zero and statistically insignificant.

Productivity seems to be falling for transformative entrepreneurs akin to the observations from Table 6.1. However, the latter estimate is not statistically significant; not every transformative firm has its productivity decline while growing.

8. Robustness checks

8.1 Patents: stock versus counts

The results so far have shown that within patent clusters productivity grows faster and the cutoff productivity is slightly higher than most other places. Together, these two effects pushed entrepreneurs in these clusters to develop a productivity advantage over other firms. One criticism to these findings can be that they rely on the instantaneous count of patents, whereas productivity and growth are mostly driven by the accumulated stock of knowledge.

In this section, I define and compute a stock measure of patents to test the robustness of the results to the definition of patent clusters. The stock definition of patents follows a perpetual inventory model of the form:

$$P_{jit}^{N} = (1-\delta)P_{jit}^{N} + \sum_k \frac{1}{p_k}\mu(d_{j,k}; 5km, 4). \tag{19}$$

The last term in is, again, the fuzzy count of patent applicants in the vicinity of firm j, where each applicant is also adjusted for her share of patent knowledge. This knowledge depreciates over time, yet gets replenished by new patent applications. The depreciation rate is set to $\delta_P = 0.05$, accounting for the fact that standard patents in Australia are valid for a maximum of 20 years.[10]

[10] See https://www.ipaustralia.gov.au/patents/understanding-patents/patent-basics.

The variable I am using in the modelling is a log transformation of the above to limit the effect of outliers and large values on the results. Formally,

$$PS_{jit} = \log\left(1 + P_{jit}^{N}\right). \tag{20}$$

Replacing the variable P in with PS, I re-estimate the coefficients and report them in Table 8.1. Comparing these results with those from Table 6.1 shows that the qualitative implications are all intact. All the findings regarding patent clusters also carries over to patent stocks.

Table 8.1 Re-estimation results using patent stocks instead of patents.

Variables	Mature	Age 1	Age 2	Age 3
C	0.098*** (0.005)	-0.028* (0.016)	-0.067*** (0.017)	0.128*** (0.018)
C^S	0.042*** (0.012)	-0.296*** (0.044)	-0.229*** (0.045)	-0.202*** (0.050)
C^C	-0.092*** (0.013)	0.119*** (0.041)	0.437*** (0.044)	-0.100** (0.048)
P	0.032*** (0.001)	-0.001 (0.003)	-0.058*** (0.004)	0.053*** (0.004)
T	–	1.021*** (0.118)	0.916*** (0.119)	0.294** (0.121)
R^2	0.060			
Adjusted R^2	0.060			
F	262.57***			
N	305,891			

Notes: Numbers in parentheses are standard errors. *** and ** indicate 1% and 5% significance levels, respectively. Inverse propensity weights are used in the estimation.

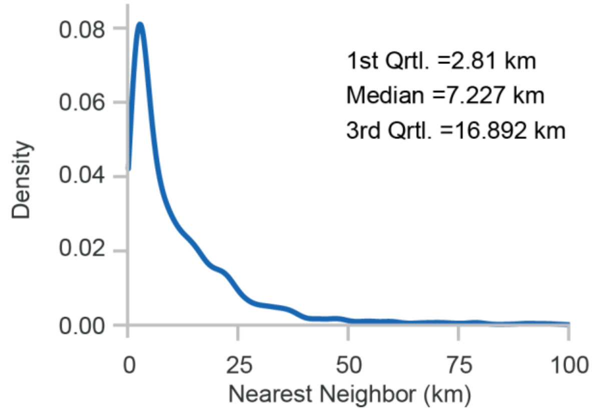
Source: Department of Industry, Innovation and Science (2018)

8.2 Geography

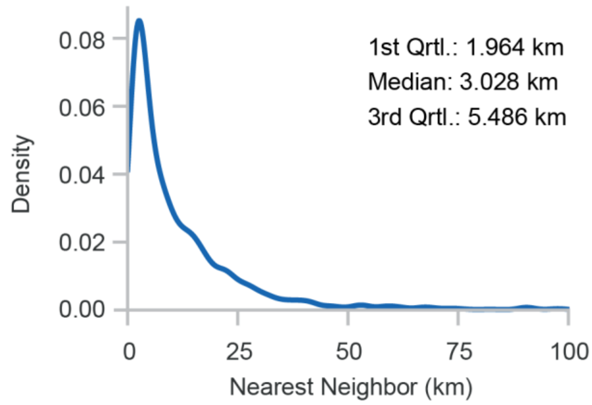
The clustering indexes used in Section 6 are based on the physical distance between the postcode centroids. As Figure 8.1(a) shows, some postcodes in Australia can be very large; the centroid of the nearest postcode in some cases is 50 kilometers away or farther. However, once weighting each postcode by the number of firms residing in it, it becomes clear that the majority of firms in the data are located within postcodes with smaller radii (Figure 8.1(b)). In the latter case, the centroid of about three quarters of postcodes is within 5 kilometers of the nearest centroid. With this revelation, it can be argued that the results in the previous sections are primarily driven by the firms residing in these smaller postcodes.

Figure 8.1 The distribution of nearest neighbour's distance across postcodes (a) unweighted, and (b) weighted by the number of firms in each postcode.

(a) Unweighted



(b) Weighted



Notes: The vertical dashed line indicates the 5km radius.

Source: Department of Industry, Innovation and Science (2018)

I still carry out a robustness test using firms residing in postcodes where the nearest centroid is at most 5 kilometers away. Using this subsample, I re-estimate the coefficients in (16). The results are presented in Table 8.2.

Table 8.2 Re-estimation results using firms in postcodes where the nearest neighbour is at most 5km away.

Variables	Mature	Age 1	Age 2	Age 3
C	0.059*** (0.009)	-0.120*** (0.030)	-0.595*** (0.032)	0.198*** (0.036)
C^S	0.042** (0.019)	-0.430*** (0.068)	-0.219*** (0.073)	-0.007 (0.078)
C^C	-0.151*** (0.021)	0.345*** (0.063)	0.808*** (0.069)	-0.222** (0.074)
P	0.036*** (0.002)	-0.024*** (0.007)	-0.058*** (0.007)	0.022*** (0.008)
T	–	0.999*** (0.124)	0.888*** (0.125)	0.225* (0.129)
R^2	0.068			
Adjusted R^2	0.067			
F	220.25***			
N	224,171			

Notes: Numbers in parentheses are standard errors. ***, **, and * indicate 1%, 5% and 10% significance levels, respectively. Inverse propensity weights are used in the estimation.

Source: Department of Industry, Innovation and Science (2018)

Comparing these results to those from Table 6.1, one observes that restricting the sample to smaller postcodes does not change the qualitative implications for any of the variables. The main difference is that, when using the smaller postcodes, the magnitude of the coefficients are larger and the statistical significances have increased.

9. Conclusion

Entrepreneurs in Australia, even those that survive, do not have much productivity advantage over the incumbent firms. The only group of entrepreneurs that show substantial productivity advantage are the transformative ones. However, their number is very small. Interestingly, the findings show that many entrepreneurs lacking an upfront productivity advantage, develop one over time. Clusters of firms and patents effectively push entrepreneurs to develop and improve their productivity. Failing to do so, they will be forced to exit. This picture suggests that productivity is not a static and inherent characteristics of the firm but one that can be shaped and developed by its surroundings. In view of the last point, there are some policy lessons on the ways to harness the power of clusters for productivity growth. For instance, government does not have to give up on low productivity firms. Exposed to proper competition, these firms could flourish. Providing the right incentive or competitive pressure can be the remedy. Research hubs and high-innovation areas offer fast productivity growth without the increased competitive stress. A policy to encourage business formation close to research and innovation hubs can also be very effective. The results of this research suggest that clustering with friendly firms, however, is not a significant force for productivity growth.

Appendix A TFP estimates

The estimated coefficients in the production function (1) using the De Loecker & Warzynski (2012) method are reported in Table A.

Table A The estimates of α coefficients in the production function (1) by industry.

ANZSIC	$\alpha^{(l)}$	$\alpha^{(k)}$	ANZSIC	$\alpha^{(l)}$	$\alpha^{(k)}$
11	1.182	0.125	19	1.194	0.073
12	0.975	0.155	20	1.240	0.136
13	1.275	0.121	21	1.200	0.169
14	1.088	0.090	22	1.091	0.100
15	0.886	0.240	23	1.113	0.111
16	1.232	0.128	24	1.118	0.120
17	1.429	0.205	25	1.365	0.089
18	1.430	0.098	ANZSIC	$\alpha^{(l)}$	$\alpha^{(k)}$

Source: Department of Industry, Innovation and Science (2018)

Disclaimer

The results of these studies are based, in part, on 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 ATO to the ABS under the Taxation Administration Act 1953. These require that such data is 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 or ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of this 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 confidentialised to ensure that they are not likely to enable identification of a particular person or organisation.

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