Entrepreneurial Dynamics and the Small-Firm Effect*

Barton H. Hamilton
Olin Business School, Washington University in St. Louis

Andrés Hincapié
Department of Economics, University of North Carolina at Chapel Hill

Mostafa Salari
Olin Business School, Washington University in St. Louis

ABSTRACT: Small-firm workers are almost thrice as likely to become self-employed as large-firm workers, and the self-employed are twice as likely to transition into small versus large firms. What explains these unbalanced dynamics? Using Australian data (2001-2019), we estimate a dynamic structural model capturing the role of human capital and its transferability across sectors, discovering one's sector-specific abilities, and non-pecuniary motivations. We find that the main drivers explaining the differential transitions into and out of self-employment from small firms are the favorable returns and transferability of large-firm experience, and the higher switching costs associated with moving between small firms and self-employment.

KEYWORDS: Entrepreneurship, Small Firms, Learning, Human Capital, Firm Size.
JEL CLASSIFICATION: J21, J24, J62

*This version: January 27, 2024. Corresponding author Andrés Hincapié; email: andres.hincapie@unc.edu.

1 Introduction

Scholars of economics consider entrepreneurship as a driving force behind economic growth and technological change (Schumpeter, 1934), and over the last three decades, a large body of research has focused on the determinants of entrepreneurship. However, entrepreneurship decisions are still not fully understood. Recent research indicates that most individuals start their businesses after accumulating experience in the paid sector (Hincapié, 2020). Moreover, the characteristics of individuals' workplaces might affect their entrepreneurial decisions and outcomes. One of these workplace features is firm size. People who work in small firms are much more likely to become entrepreneurs than those in large firms (Wagner, 2004; Sørensen, 2007; Elfenbein et al., 2010); conversely the self-employed are more likely to become small-firm workers than large-firm workers.[1] This "small-firm effect" raises the following questions: How does the accumulation of experience in small and large firms affect entrepreneurial entry and exit decisions and returns? Do small firms "incubate" future entrepreneurs?

To address these questions, we develop and estimate a dynamic model of career choices in which risk-averse individuals choose sequentially between self-employment (SE), paid employment in a small firm (PS), paid employment in a large firm (PL), or not working (NW). At the beginning of their career, individuals only know the education-specific distribution of ability in the population. Subsequently, through their sectoral choices, individuals update their beliefs about their sector-specific ability. In each period, the agents choose a sector based on expected income and non-pecuniary factors (including disutility from income uncertainty), taking into account the impact of current choices on future decisions. Using the estimated model on Australian panel data, we simulate decisions and returns under different counterfactual scenarios to quantify the role of different mechanisms identified in the literature as explanations for the small-firm effect.

Our results indicate that small firms do not disproportionately spawn highly successful startups. The small-firm effect we see in the data reflects two main factors. First, human capital acquired in small firms offers less returns, which lowers the opportunity costs from switching from small-firm work into self-employment. Consequently, a higher share of small-firm workers enter self-employment and these entrants posses, on average, lower ability than those entering from large firms. Second, individuals sort between small firms and self-employment based on how similar their preferences for both of these sectors are, including the switching costs associated with them. This is consistent with the idea that small firms and self-employment offer similar levels of job autonomy and task variety that individuals find appealing.

Studies in the literature propose two categories of explanations for the small-firm effect (Elfen-

[1] A number of studies in management and strategy show how employer characteristics may induce the "spawning" of new startups by former employees, particularly in high tech industries. See Klepper (2009) for a review of this literature.

bein et al., 2010): treatment-based and selection-based. The former refers to the transferability of small-firm skills to entrepreneurship, while the latter emphasizes preference-based sorting across sectors. We emphasize three key characteristics of our model designed to distinguish between these sets of explanations. First, skills acquired while working in small firms may be more transferrable to running a business than those acquired by working in a large firm. According to Lazear (2005), an entrepreneur is a "jack-of-all-trades" that needs to do a variety of tasks. Similarly, small-firm employees also need to perform more diverse tasks than workers in large firms (Molina-Domene, 2018). Small-firm employees may also have access to valuable networks critical to entrepreneurship (Stuart and Ding, 2006) or may be able to enjoy positive spillovers from more entrepreneurial coworkers (Wallskog, 2023). In line with Lazear's theory, a small-firm environment might then be more suitable for acquiring entrepreneurial human capital. We thus allow human capital to accumulate through *learning-by-doing* and test whether skills accumulated in small and large firms are transferable to self-employment, where they potentially have different impacts on self-employment earnings.

The second key feature of the model is accumulation of information through the process of *learning-about-ability*. Here we define ability as a permanent person-specific component of sectoral earnings. Most studies assume that learning-about-ability is independent across sectors, implying that working in a small firm conveys no information about an individual's ability in entrepreneurship.[2] In such frameworks the only way for an individual to learn about their entrepreneurial ability is by actually becoming self-employed (Jovanovic, 1979; Antonovics and Golan, 2012; Dillon and Stanton, 2017). We depart from this independence assumption by allowing learning-about-ability to be correlated across sectors. In our correlated learning framework, working in one sector is potentially informative about the individual's ability in all sectors (James, 2011; Hincapié, 2020). Therefore, a would-be entrepreneur might initially choose to work in a small firm if self-employment ability is more strongly correlated with small-firm ability.

Finally, we incorporate non-pecuniary benefits into our model. Non-pecuniary benefits, such as autonomy, can incentivize self-employment (Hamilton, 2000; Hurst and Pugsley, 2011, 2017) since individuals may want to "be their own boss." It has been documented that small-firm employees also have more freedom of action (Brown and Medoff, 1989; Sørensen, 2007) than large-firm workers. Åstebro and Thompson (2011) argue that entrepreneurs may prefer to engage in a variety of tasks, which is also required in small firms. As a result, potential entrepreneurs might choose to start their careers in small firms and switch to self-employment subsequently based on preferences for the similar attributes of self-employment and small firms. Using our estimates of switching costs, we are able to test whether the non-pecuniary benefits of entering self-employment from a

[2]The independence assumption implies that working in a sector provides no extra information about an individual's ability in any other sector (Miller, 1984; Pavan, 2011).

small firm are greater than that from a large firm as suggested by the literature.

We estimate the model using the Household, Income and Labour Dynamics in Australia (HILDA) longitudinal data, waves 1 (2001) through 19 (2019). For our study, the unique feature of the HILDA data is that it collects the number of employees at the individual's workplace at all locations throughout Australia in every wave. Using the HILDA dataset, we construct a sample of males observed from the beginning of their labor market careers. We group the paid-employment sectors into small (less than 100 employees) and large (100 or more employees) firms. We observe and document the small-firm effect in HILDA. The data shows that small-firm employees are about three times more likely to become self-employed than large-firm employees (Table 3). We also document a small-firm effect on the exit margin: entrepreneurs are more than twice as likely to move to a small firm when leaving self-employment.

Given that learning-about-ability is correlated across sectors in our model, joint maximization of model parameters comes at a substantial computational cost. To overcome these computational difficulties regarding the estimation of the model, we apply the Expectation-Maximization (EM) algorithm and estimate the model in two stages (James, 2011). The EM algorithm eliminates the need to perform high-dimensional integration and delivers a closed-form solution to recover consistent estimates of the income and ability distribution parameters in a first stage. Using the first-stage parameters and applying Bayes' rule, we recover the individual beliefs. In the second stage, we treat the beliefs as data and use the first-stage estimates to recover the structural utility parameters. We then use these structural parameters to conduct a variety of counterfactual analyses to assess alternative explanations for the small-firm effect.

As summarized earlier, our empirical results reveal that the small-firm effect arises primarily from two factors. First, compared to human capital acquired in large firms, human capital acquired in small firms has lower returns and offers lower earnings growth, thus reducing the opportunity cost of entering self-employment from small firms. Using our model estimates, we conduct counterfactual simulations in which small-firm returns to human capital are set equal to their large-firm counterparts. Under this counterfactual, workers in small and large firms are now equally likely to become entrepreneurs, and overall self-employment rates substantially decline. The exit rate out of self-employment to small-firms (relative to large firms) also increases substantially, since human capital offers substantially higher returns in small firms under this scenario. In addition, while we find that education plays an important role in entrepreneurial returns (Ehrlich et al., 2017), similar patterns of movement between small firms and self-employment are found for both college and non-college graduates. Overall, opportunity costs are thus an important factor in explaining the small-firm effect.

Our findings also highlight a second key factor: the role of sorting on preferences into entrepreneurship. After accounting for income effects and risk aversion, our utility function estimates show that the non-pecuniary benefit of switching between working in a small firm and entrepreneurship is substantially higher than the switching cost from moving between a large firm and self-employment. When we conduct a counterfactual simulation in which we equalize these switching costs (set to the large-firm level), the fraction of individuals trying self-employment by age 40 drops substantially, from 40% to 25%; most of this decline reflects a substantial reduction in the probability of moving from a small firm to self-employment. These findings are consistent with entrepreneurship and small-firm employment offering similar levels of non-wage characteristics (e.g. autonomy) that are valued by individuals, thus contributing to generate the observed small-firm effect.[3] We also find that preferences are a much more important driver of self-employment entry (and exit) than other factors, such as wealth. Moving from the lower quartile to the upper quartile of the initial wealth distribution in our sample only increases the fraction of individuals trying self-employment by age 40 from 37% to 41%.[4]

We contribute to the growing literature on learning and entrepreneurial dynamics. In this literature, our paper is closest to Hincapié (2020), who studies the relationship between occupational choice (blue-collar vs. white-collar) and self-employment in the U.S. to understand why there are so few young entrepreneurs as might be predicted by learning models (e.g., (Miller, 1984)). However, unlike Hincapié (2020), we have data on firm size and so can address the role that small (and large) firm experience plays in entrepreneurial entry, exit, and returns that has been discussed in papers such as (Elfenbein et al., 2010). Our results for Australia reject the idea often found in the literature that abilities are uncorrelated across sectors. In our data, high (low) ability employees in either sector tend to be high (low) ability entrepreneurs; this strong positive correlation (generally about 0.6) is similar across firm size and education groups. Because paid employment exhibits lower levels of idiosyncratic earnings variance, risk-averse individuals may then choose to begin their careers in small or large firms as an indirect, yet low risk way to learn about their entrepreneurial ability. For example, we show that 5 years of small (large) firm experience for a college graduate reduces uncertainty about entrepreneurial ability by approximately 30% (28%), compared to a reduction of 72% for the same level of self-employment experience. Learning-about-ability thus appears to be similar in both small and large firms and unlikely to contribute to the small-firm effect. In a counterfactual assuming individuals have full information about their abilities, so that learning-about-ability is not a factor in explaining entrepreneurial dynamics, the small-firm effect narrows only slightly. Moreover, selection of individuals from small and large firms into entrepreneurship increases proportionately.[5]

[3]Survey evidence from HILDA participants in Table 1 indicates that small-firm workers experience more autonomy and use a wider variety of skills than their large-firm counterparts.

[4]Consistent with the view that wealth may affect the scale of the business (rather than entry or exit), we find that wealthier individuals start businesses generating more income.

[5]Under our full information counterfactual, the average ability of self-employment entrants from small (large) firms

Finally, our findings have implications for the impact that large firms have on entrepreneurship. Entrepreneurs “spawned” by large firms tend to be more able and earn more, which is consistent with the greater opportunity costs these entrants face. In addition, our estimates provide and assessment of the transferability of human capital from small and large firms into self-employment. We find that the return to large-firm experience is in fact higher than that of small-firm experience in self-employment, and that entrepreneurial experience is more valuable than small-firm experience (in some cases) when employed by a large firm. One explanation for these findings is that large-firm managers have greater spans of control and more supervisory responsibilities than individuals in small firms (Fox, 2009). This type of human capital may be particularly valuable in a startup. Conversely, entrepreneurs may gain the leadership skills required for roles in larger firms. Unfortunately, these individuals are reluctant to start their own businesses, since they experience a switching costs when they transition from a large firm to self-employment.

This paper proceeds as follows. Section 2 describes the HILDA data, establishes descriptively the small-firm effect, and provides relevant facts for our model selection. Section 3 describes the model detailing the features that capture the main hypothesized mechanisms for the small-firm effect. Section 4 discusses the identification and estimation strategy and provides evidence on model fit. The estimates presented in Section 5 facilitate our discussion of the profiles of returns to experience in each sector, the correlation of skills across sectors, the opportunities for paid-employees to learn about their entrepreneurial abilities, and the various sectoral preferences. Section 6 contains the counterfactual experiments we use to quantify how much the different mechanisms in the model contribute to explain the observed small-firm effect. Section 7 concludes.

2 Data

Our data come from the Household, Income and Labour Dynamics in Australia (HILDA) survey, a nationally representative household-based panel study which started in 2001 and follows more than 17,000 Australians each year. We use information regarding employment status, annual working weeks, labor and business income, wealth at the beginning of the labor market career, number of employees at the workplace, and demographics, including age, education, and father’s education and occupation. Our sample covers years 2001 to 2019, and after data cleaning it contains 3,098 unique men and 18,535 individual-year observations.[6] (See Appendix A.1 for details of the cleaning process.) We split the paid-employment sector using firm size into small firms (less than 100 employees) and large firms (100 or more employees). The resulting, mutually exclusive

is 3.0 (2.8) times higher compared to the baseline.

[6] In order to leverage as much data as possible, we allow for observations to have missing values in father’s occupation (13%) and in father’s education (12%) and incorporate indicators for missing information in estimation; 20% of observations have missing in at least one of these two variables.

working status categories are: unemployed or not in the labor force (NW), small-firm workers (PS), large-firm workers (PL), and self-employed (SE). Throughout the paper we interchangeably use the terms entrepreneurship and self-employment.

Although the threshold of 100 employees to define firm size has been used in previous studies (Ayyagari et al., 2011), it can still seem rather arbitrary. To provide evidence of the empirical content of the distinction created by the threshold we first exploit data on workers' assessments regarding the characteristics of their jobs. Table 1 shows that meaningful and statistically significant differences exist between small and large firm jobs. While large firm jobs tend to be more complex and require more up-to-date skills, small-firm jobs tend to use a wider variety of skills and offer more freedom of action. In addition, Table 1 also shows that self-employment tends to dominate in all regards: complexity, variety of skills employed, and freedom of action; in the latter, self-employment is substantially superior.

Table 1: Job Characteristics: Individual Assessments

Statement	Self-Employment	Small-Firm	Large-Firm
I use many of my skills and abilities in my current job	5.65	5.42*	5.34*
I have a lot of freedom to decide how I do my own work	5.81	4.72*	4.59*
I have a lot of say about what happens on my job	5.88	4.53*	4.24*
I have a lot of freedom to decide when I do my work	5.32	3.55*	3.45*
I have a lot of choice in deciding what I do at work	5.48	3.81*	3.70*
I can decide when to take a break	5.86	4.68*	4.79*
My working times can be flexible	5.44	4.12*	4.01*
My job is complex and difficult	4.51	4.35*	4.50
My job often requires me to learn new skills	5.05	4.90*	5.12
My job requires me to do the same things over and over again	4.89	4.72*	4.67*
My job provides me with a variety of interesting things to do	5.20	4.77*	4.75*
My job requires me to take initiative	6.01	5.54*	5.54*
Observations	1,091	4,443	6,592

Notes: The sub-sample includes individual-year observations with answers to all questions. The range of values for each statement is integers from one (strongly disagree) to seven (strongly agree). The asterisk indicates that the difference in means relative to self-employment is significant at the 95% level. All differences between small-firm and large-firm means are significant at the 99% level except for the last three rows.

Table 2 provides further details of our individual-year observations by sector, highlighting a number of key features in the data. Among workers, average annualized income is lowest for small-firm workers at 57,300 Australian dollars (AUD), which is consistent with prior research documenting lower compensation in small firms (Brown and Medoff, 1989).[7] Large-firm workers

[7] Annualized income is obtained as follows: for working individuals, reported annual income is divided by the number of weeks reported working, this number is then multiplied by the sector-specific average of working weeks; for non-working individuals, reported annual income is divided by the number of weeks reported receiving government allowances, this number is then multiplied by the average number of weeks receiving government allowances among those not-working. We use annualized income as we do not model the number of weeks worked per year. In that sense, we focus on the contribution of experience on the returns to one unit of effective labor.

Table 2: Sample Descriptives per Sector: Working-Age Young Australians

	Self-Employment	Small-Firm	Large-Firm	Not-Working	Total
Annualized income (1,000 AUD)					
Overall	71.7	57.3*	76.9*	9.9*	66.5
	(80.3)	(33.0)	(49.8)	(3.6)	(49.8)
Less than college	64.9	55.6*	69.0*	9.9*	60.1
	(58.8)	(29.7)	(38.3)	(3.7)	(39.3)
College or more	101.0	64.8*	92.6	9.3*	85.2
	(135.6)	(44.0)	(64.3)	(2.0)	(68.8)
Small-firm experience	1.9	3.9*	0.9*	0.9*	2.0
	(2.7)	(3.2)	(1.9)	(2.0)	(2.9)
Large-firm experience	0.9	0.9	4.8*	0.7*	2.7
	(2.0)	(2.0)	(3.8)	(1.8)	(3.6)
Self-employment experience	3.83	0.20*	0.11*	0.21*	0.50
	(3.22)	(0.89)	(0.68)	(1.28)	(1.65)
Age	28.0	27.1*	28.8*	25.9*	27.6
	(4.6)	(4.3)	(4.5)	(3.9)	(4.5)
College or more	0.19	0.19	0.34*	0.09*	0.25
Initial wealth (1,000 AUD)					
Median	204.6	116.0	142.7	47.3	131.0
Mean	632.7	489.2*	534.4*	346.2*	510.3
	(1259.6)	(1051.6)	(1014.6)	(956.2)	(1049.1)
Father's characteristics:					
White collar	0.80	0.68*	0.73*	0.58*	0.71
High-school or more	0.39	0.40	0.48*	0.35*	0.44
Observations	1709	6410	8693	1723	18,535
%	9.2	34.6	46.9	9.3	100

Notes: Standard deviation is in parentheses. The asterisk indicates that the difference in means relative to self-employment is significant at the 95% level. Monetary values are in real AUD of 2015. Individuals in the sample are between 22 and 41 years old. Annualized income is obtained as follows: for working individuals, annual income reported in HILDA is divided by the number of weeks reported working, this number is then multiplied by the sector-specific average of working weeks; for non-working individuals, annual income reported in HILDA is divided by the number of weeks reported receiving government allowances, this number is then multiplied by the average number of weeks receiving government allowances among those not-working. Average annualized income for the non-working is conditional on receiving any income. Initial wealth is the individual's wealth at the beginning of their labor market career. Initial wealth in the individual's wealth at the beginning of their labor market career. *White collar* indicates whether the respondent's father was in a white collar occupation when respondent was 14 years old. Father's descriptives are conditional on not missing data. In our final sample 13% of observations have missing values in father's occupation and 12% have missing values in father's education. We keep these observations and add missing indicators in estimation.

and entrepreneurs earn 34% and 25% more, respectively. Self-employment exhibits substantially higher variation in income, much more so among individuals with college or more. This high variation in income can reflect both greater variation in entrepreneurial ability and greater idiosyncratic income variation (e.g. luck). In Australia, non-working individuals can receive income from government allowances. In our sample, 41% of non-working observations did receive income from these allowances; among these individuals both average annualized income (9,900 AUD) and income variation are low. Median initial wealth (at the beginning of the individuals' labor market careers) is the largest for individuals engaged in self-employment (204,600 AUD), with a value 43 percent higher than large-firm workers and 76 percent higher than small-firm workers.[8] These differences in initial wealth are consistent with initial resources being a determinant of occupational choices.

Consistent with the hypothesis of a small-firm effect, Table 2 also reveals that self-employed individuals have more than twice as much prior small-firm experience (1.9 years) than large-firm experience (0.9 years). In addition, our summary statistics show that the self-employed tend to be older than small-firm workers, and that large-firm workers have more years of education. Finally, the family background of the self-employed is also different. While their fathers have similar education as small-firm workers' fathers, the self-employed's fathers are at least 10 percent more likely to have been white-collar workers than the paid-employees' fathers.

The data also reveal four main stylized facts documenting the self-employment dynamics and the small-firm effect. First, Figure 1 shows that as individuals age they move into the labor market, out of the small-firm sector, and into the large-firm and self-employment sectors. Overall, the right panel of Figure 1 shows that the share of self-employment increases steadily from 5% at age 22 to about 18% at age 40. The middle and left panels of Figure 1 show that this trend in self-employment participation is similar for those with less than college, who start their careers with lower labor market attachment (as measured by the share not working), and for those with college or more.[9] The share of individuals working in small firms falls steadily for all individuals but the decline is larger for those with college or more, going from about 34% at age 22 to about 18% by age 40. Finally, while participation in large firms increases over the life cycle, this trend reverses in the mid thirties for those with less than college, widening the gap in large-firm work relative to those with college or more, a gap that remains above 20 percent points throughout their careers.

Second, the small-firm effect is evidenced in both the entry and exit margins of self-employment. Table 3 shows that small-firm workers are more than three times as likely as large-firm workers to switch into self-employment (1.4 vs 4.6 percent); in the opposite direction, the self-employed are twice as likely to enter the small-firm sector as they are to enter the large-firm sector (11.4 vs 5.6 percent). Further descriptives in Table A.2 (Appendix A.2) also show that while about two thirds of the transitions into self-employment from small-firm work are within the same industry, only about one third of the transitions from large-firm work into self-employment are within the same industry.[10]

[8] Wealth in HILDA is measured at the household level. Our initial wealth measure thus includes the wealth of other household members, such as the spouse or parents.

[9] Our numbers of not-working young individuals are consistent with Todd and Zhang (2020) who also study the Australian labor market.

[10] Focusing on healthcare occupations, Table A.3 in Appendix A.2 shows that among individuals with high education, nine percent of all same-occupation transitions from small-firm work into self-employment are transitions within healthcare occupations.

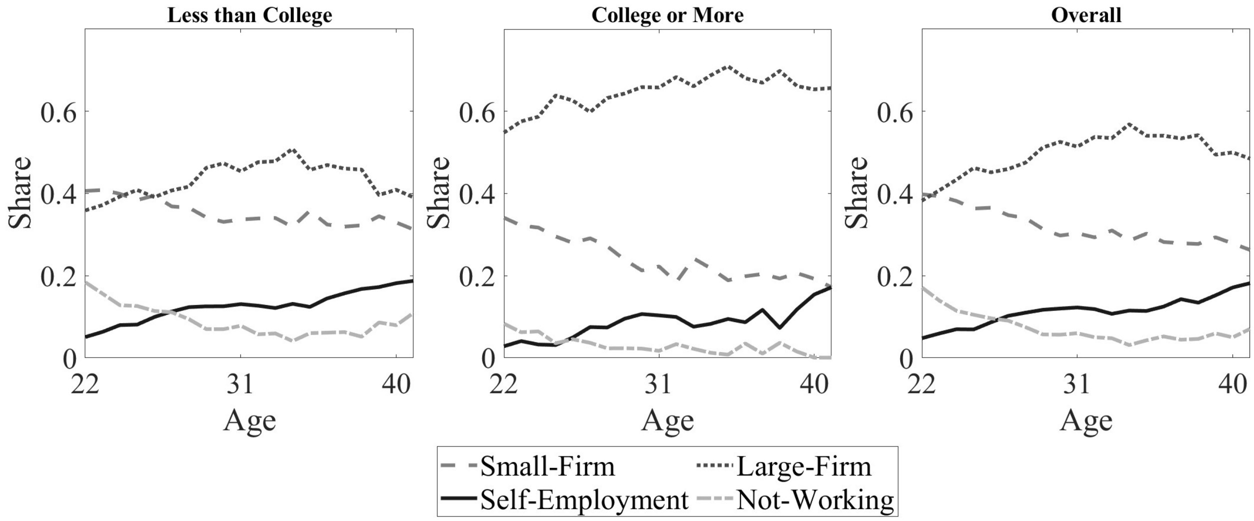


Figure 1: Sector Choice: Participation by Age and Education Level
Notes: *Small-Firm* and *Large-Firm* correspond to salaried workers in small and large firms, respectively.

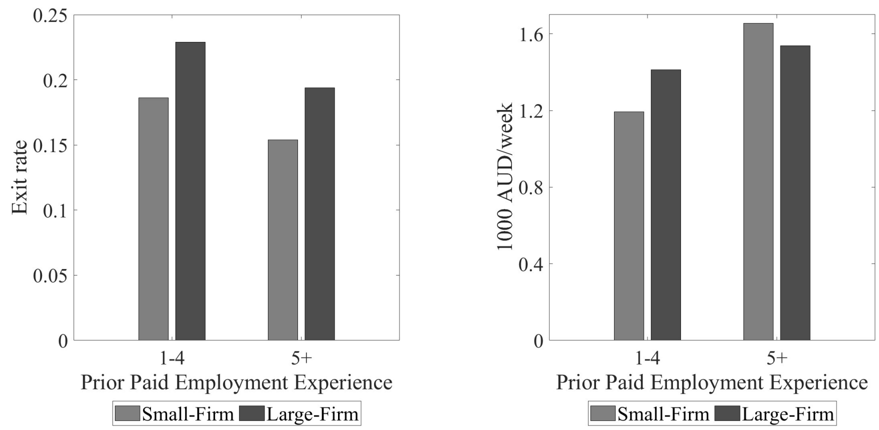
Third, consistent with findings in Hincapié (2020) for the U.S., our data of the Australian labor market reveal that paid-employment experience acquired before first trying self-employment is negatively correlated with exit and positively correlated with income. Figure 2(a) reveals a negative association between prior experience in either firm-size sector and the exit rate out of self-employment. Notably, prior experience in the small-firm sector is associated with a lower exit probability at both levels of prior experience. Figure 2(b) shows that prior experience in paid-employment of either type is positively correlated with self-employment income. The gradient of these associations exhibits decreasing returns for large-firm experience and increasing returns for small-firm experience.

Table 3: Transition Matrix

	Self-Employment	Small-Firm	Large-Firm	Not-Working
Self-Employment	80.2	11.4	5.6	2.8
Small-Firm	4.6	76.8	14.2	4.3
Large-Firm	1.4	9.2	86.7	2.7
Not-Working	3.8	19.8	16.8	59.7

Notes: Matrix element (i, j) represents the percent of people in sector in row i who move into sector in column j between t and $t+1$.

Our summary statistics and empirical regularities document the distinction between small- and large-firm work as well as the apparent small-firm effect on entrepreneurship dynamics. These regularities also suggest possible mechanisms through which the small-firm effect operates, such as human capital and preferences. In the next section we describe our model, which aims to control for endogenous sector selection, capturing the effect of the various mechanisms behind individuals sector choices.



(a) Exit from Self-Employment (b) Self-Employment Income

Figure 2: Prior Paid-Employment Experience and Self-Employment Exit and Income

Notes: Both figures result from linear regressions of exit from self-employment and self-employment income during the first spell of self-employment. The regressions control for cross-sector prior experience and education. Figure 2(a) plots the constant plus the contribution to the exit probability from each cross-sector experience indicator. Figure 2(b) plots the constant plus the contribution to self-employment weekly income from each cross-sector experience indicator.

3 A Model of Sector Choice with Learning

We develop a dynamic discrete choice model of sector selection. Risk-averse individuals base their choices on various factors: their sector-specific, time-invariant ability, the future returns from the experience they accumulate in each sector and from initial wealth, and their preferences for each alternative. Individuals do not have certainty regarding their sector-specific ability and use residual variation in income to infer it. Preferences, experience, and information accumulation have a cross-sector property: workers in different paid-employment sectors draw different utility from entering self-employment, experience from one sector offers returns in others, and information obtained in one sector refines beliefs about individual ability in other sectors.

Sectors, individual characteristics and initial wealth. The structure of our model borrows from Hincapié (2020). Young individuals enter the labor market at age t_0 and at every age $t \in \{t_0, ..., T\}$ choose a sector $j \in \{0,1,2,3\}$. They can work at a small firm ($j = 1$), work at a large firm ($j = 2$), be self-employed ($j = 3$), or abstain from working ($j = 0$). Let $d_{jt} \in \{0,1\}$ be an indicator that takes the value of one if an individual chose alternative j at t, and let $d_t \in \{0,1\}^4$ be the vector with jth component d_{jt}. Experience $x_t \in \mathbb{Z}^3_+$ is a 3-dimensional vector capturing the individual's experience in each sector. Individuals enter the labor market with no sector experience ($x_{jt_0} = 0$) and the evolution of x_t is given by:

$$x_{jt+1} = x_{jt} + d_{jt} \tag{1}$$

for $j \in \{1,2,3\}$. Individual characteristics are collected in the vector h_t including experience, education, and father's characteristics. Also included in h_t is the individual's wealth at the beginning of their labor market career, which is exogenous to sector choices made after he enters the labor market. By integrating initial wealth as a permanent individual characteristic we capture the effect of wealth on sector choices parsimoniously, without having to model the process of individual wealth accumulation.[11] While this is clearly a simplifying modeling choice, there is a high correlation between initial wealth and future wealth (0.38 in levels). This is important because we use initial wealth as a means to capture indirectly the effect of credit constraints on sector choices (e.g. small-firm workers who have less capital might be less likely to open or grow their businesses).

Income. Individuals who participate in any of the working sectors ($j > 0$) obtain annual income at the end of the period which results from multiplying weekly income y_{jt} by the inelastic labor supply in sector j, $\bar{w}_j$.[12] Individuals who do not work may receive annual income from government allowances at the end of the period. Let $v_t \in \{0,1\}$ be an indicator of whether a non-working individual receives government allowances.[13] If so, their annual income results from multiplying the generosity of weekly income from government allowances y_{0t} by the inelastic supply of allowances $\bar{w}_0$. Hence, weekly income from choosing alternative j is given by:

$$y_{jt} = \begin{cases} f_j(h_t^y; \theta_j) + \mu_j + \sigma_j \eta_{jt} & \text{if } j > 0 \\ v_t \cdot \left(f_j(h_t^0; \theta_j) + \sigma_j \eta_{jt} \right) & \text{if } j = 0 \end{cases} \tag{2}$$

where $x_t \in h_t^y \subset h_t$, $x_t \notin h_t^0 \subset h_t$, and $f_j(\cdot;\theta_j)\ \forall j$ are parametric functions. For all individuals weekly income is a function of a subset of individual characteristics and a standard Normal idiosyncratic income shock η_{jt}, independent across alternatives, periods and individuals. Parameters σ_j capture the level of idiosyncratic variation in each sector. Four features distinguish weekly income when working. First, it is a function of the experience vector $x_t \in h_t^y$ which allows for cross-occupation returns to experience. Second, it is augmented by the individual's sector-specific ability $\mu_j \in \mu$, and $\mu \subset \mathbb{R}^3$ is distributed multivariate Normal$(\mathbf{0}, \Delta)$. Third, it is a function of the individual's initial wealth which in the case of self-employment captures potential credit constraints affecting the scale and returns of the business. Finally, there is no uncertainty regarding income availability. By contrast, individuals who do not work receive government allowances with probability $q_t(h_t^v) \in [0,1]$, where $h_t^v \subset h_t$ flexibly captures the eligibility and accessibility of welfare

[11] The data and model complexity required to handle wealth accumulation in an environment with learning about ability, while very interesting, is beyond the scope of the current paper.

[12] We model weekly income as we do not model the decision of working hours and our best measure of income per unit of time is weekly income. See Appendix A.

[13] This indicator captures the fact that not-working individuals do not always receive government allowances. In our sample only 41 percent of observations of not-working individuals have positive government allowances.

policies as a function of age and education.

Learning. Individuals do not observe their sector-specific ability separate from the idiosyncratic income shocks, but they use residual income $\mu_j + \eta_{jt}$ to form beliefs about their sector-specific ability using Bayes' Rule. Individuals have rational expectations so their initial priors $\mathbf{B}_{t_0}$ correspond to the population distribution of ability $N(\mathbf{0}, \Delta)$. Under the distributional assumptions made, the posterior beliefs $\mathbf{B}_t$ are always Normal and can be fully characterized by the mean vector $\mathbf{E}_t \in \mathbb{R}^3$ and the 3×3 variance-covariance matrix $\mathbf{V}_t$, so that $\mathbf{B}_t = (\mathbf{E}_t, \mathbf{V}_t)$. Posterior beliefs at any $t > t_0$ are updated according to the following Bayesian updating rules (DeGroot, 1970; James, 2011):

$$\begin{aligned} \mathbf{E}_t &= \left[\mathbf{V}_{t-1}^{-1} + \Sigma_{t-1}\right]^{-1} \left[\mathbf{V}_{t-1}^{-1}\mathbf{E}_{t-1} + \Sigma_{t-1}\zeta_{t-1}\right] \\ \mathbf{V}_t &= \left[\mathbf{V}_{t-1}^{-1} + \Sigma_{t-1}\right]^{-1} \end{aligned} \tag{3}$$

where the 3-dimentional signal vector ζ_{t-1} and the 3×3 diagonal weighting matrix Σ_{t-1} are given by their j-th component and (j, j) diagonal component, respectively:

$$\zeta_{jt-1} = d_{jt-1} \cdot \left(y_{jt} - f_j(h_t)\right) \qquad\qquad \Sigma_{(j,j)t-1} = d_{jt-1}/\sigma_j^2 \tag{4}$$

There are two important features of the updating rules in (3). First, they are written in the matrix, general form because the prior variance-covariance matrix $\mathbf{V}_t$ can be non-diagonal. This results from the fact that the sector-specific abilities may be correlated in the population (matrix Δ may be non-diagonal). Second, beliefs remain unchanged for individuals who do not work as not-working income is not a function of sector-specific ability, which renders it uninformative in the beliefs formation process.

Utility. The flow utility from choosing sector j, denoted u_j, depends on consumption, individual characteristics, and non-pecuniary sector-specific preference shocks ε_{jt} distributed Type I Extreme Value, independent across alternatives, periods and individuals. There is no savings mechanism so individual consumption equals annual income. The flow utility from choosing sector j, net of the preference shock, is given by:

$$u_{jt}(y_{jt}, h_t, d_{t-1}) = -\alpha_y \exp(-\rho \bar{w}_j y_{jt}) + \alpha_{jt}\left(h_t, d_{t-1}\right) \tag{5}$$

where $\rho \in [0,\infty)$ is the constant absolute risk aversion and the sector-specific non-pecuniary benefits α_{jt} are given by:

$$\alpha_{jt}(h_t, d_{t-1}) = \begin{cases} \alpha_{j1} h_t^u + \sum_{j'=1}^{3} \alpha_{j2}^{j'} d_{j't-1} & \text{if } j > 0 \\ \alpha_{02} d_{0t-1} & \text{if } j = 0 \end{cases} \tag{6}$$

The non-pecuniary benefits from working ($j > 0$) depend on a subset h_t^u of the individual characteristics (coefficients α_{j1}) and on previous sector choices (coefficients α_{j2}), the latter term capturing switching costs. For identification purposes the non-pecuniary benefits from not-working are normalized to zero except for the non-pecuniary benefits from continuing to not work (α_{02}).

Optimal sector choices. Individuals have discount factor β and they choose a sector to maximize expected lifetime utility before knowing whether not-working income will be available for them. Hence, the state of the individual's problem $z_t = (h_t, d_{t-1}, \mathbf{B}_t)$ contains experience and other individual characteristics in h_t, lagged choices d_{t-1}, and prior beliefs $\mathbf{B}_t$. The conditional value of choosing sector j at any period t, net of the preference shock, is given by:

$$v_{jt}(z_t) = E\left[u_{jt}(y_{jt}, h_t, d_{t-1}) + \beta V_{t+1}(z_{t+1}) \,|\, z_t, d_{jt} = 1\right] \tag{7}$$

where $V_t(z_t)$ is the value function of the problem, which is standard. Importantly, the expectation in (7) is computed using the prior beliefs included in z_t and it includes the changes in beliefs that will ensue from receiving additional information in the working sectors.

Optimal choices capture the learning-by-doing incentive to accumulate experience in sectors with high own- and cross-sector returns. For instance, individuals may be more willing to acquire experience in a low-risk sector, before experimenting with a high risk sector, if that experience offers non-negligible cross-sector returns in the high-risk sector. Optimality also captures different non-pecuniary incentives to move across sectors (switching costs). For instance, small-firm workers may draw more utility from switching into self-employment than large-firm workers. Finally, optimal sector choices entail a trade-off between risk aversion and learning-about-ability. On the one hand, risk aversion pushes individuals away from sectors with higher income risk (such as self-employment). On the other, the information value of sectors with large variation in ability draws individuals to the sector to find out their position in the distribution. Correlated learning allows individuals to choose a path with lower income risk while reducing uncertainty about their ability in sectors with higher income variance.

4 Identification and Estimation

Identification. The parameters to be identified are the variance-covariance matrix of the population distribution of sectoral ability Δ, the income process parameters $\Theta = \{\theta_0, \sigma_0, \ldots, \theta_3, \sigma_3\}$, the parameters of the probability of not-working income denoted Γ, and the utility parameters denoted Λ. The distribution of taste shocks has variance one and location parameter zero. The discount factor is set at $\beta = 0.95$. The sources of variation are panel data containing individual sectoral choices, sectoral income, and demographic characteristics including initial wealth. Identification of most of the parameters mentioned above in a dynamic sector-choice setting with selection on beliefs, under the normality and rational expectations assumptions, is discussed in Hincapié (2020). It is worth mentioning that in our framework observed transitions between sectors in the panel help us identify the targeted switching costs in the utility function, while other flow non-pecuniary utility parameters associated with age and father's background are identified relative to their not-working counterparts, which are normalized to zero. The conditional probability of not-working income and the conditional expectation of not-working income given that any is received are identified using variation in the extensive and intensive margins of not-working income. This variation is a function of the government's eligibility and generosity policies regarding not-working income allowances. Importantly, we assume that sector ability does not affect whether individuals receive not-working income or how much they receive.

Empirical implementation. To facilitate implementation of the model while still capturing the relevant mechanisms we adopt the following specifications presented in more detail in Appendix A. Entry age into the labor market $22 \leq t_0 \leq 27$ is determined using the individual's potential experience. Since initial wealth is right-skewed and it contains negative and zero values, instead of the level of initial wealth we use its inverse hyperbolic sine transformation to flexibly integrate its effect (Friedline et al., 2015; Pence, 2006). The population distribution of sector ability Δ and the idiosyncratic variance of working-income (σ_j^2 for $j > 0$) varies by education level (less than college or college and above). The sector-specific inelastic labor supply $\bar{w}_j$ is defined as the average number of weeks among those who work in sector j. The inelastic supply of government allowances $\bar{w}_0$ is defined as the average number of weeks in which non-working individuals received government allowances, conditional on receiving any. Besides sector experience x_t, the vector of individual characteristics h_t contains age, education level, initial wealth, father's education level (less than high school or high school and above), and father's occupation (white collar or blue collar) when the individual was 14 years old. For each of the working sectors $j > 0$, the vector h_t^y determining weekly income contains the individual's education, initial wealth, and a step function of own- and cross-sector experience. Hence, experience in sector j is allowed to have non-zero returns in other sectors $j' \neq j$. For not-working individuals, the vectors h_t^v and h_t^0 which determine the extensive and intensive margins of weekly income contain a polynomial of age and education. The probability of obtaining government allowances conditional on choosing not to work $q_t(h_t^v)$ is specified as a probit model. The vector of utility-relevant characteristics h_t^u contains own age, initial wealth, and father's characteristics, which captures variation in the non-pecuniary benefits to be self-employed over the life cycle and variation in the propensity to become self-employed depending on one's monetary resources and father's characteristics (Hout and Rosen, 2000; Hundley, 2006). Since the highest age in the estimation sample is 41, we leverage the variation in our sample while still allowing the life cycle profile of labor market participation to be completed.[14] Similar to the approach used in Todd and Zhang (2020), individuals make sector decisions until age $\bar{t} = 49$ and for every age $\bar{t} < t \leq T$ they remain in the same sector they chose at $\bar{t}$. The continuation value upon retirement is normalized to zero, $V_{T+1}(z_{t+1}) \equiv 0$.

Estimation and model fit. We take advantage of the additive separability of the log-likelihood function and estimate the parameters of the model using a two-stage process. In the first stage we estimate the parameters of the extensive and intensive margins of not-working income (Γ, θ_0 and σ_0) and we use an Expectation-Maximization (EM) algorithm to estimate the variance-covariance matrix of sector ability (Δ) and the parameters of the income process in working occupations (Θ). In the second stage we take the first-stage parameters as given and maximize the log-likelihood of the observed sectoral choices to estimate the utility parameters (Λ). Since our preference disturbances ε_{jt} are distributed Type I Extreme Value the conditional choice probabilities given a candidate vector of utility parameters are a known function of the conditional value functions. The conditional value functions are obtained by solving the dynamic model backwards under the candidate parameter vector. Standard errors are corrected for the two-stage estimation process using subsampling over 100 subsamples without replacement. Further details about the estimation procedure are in Appendix B.

Figures 3 and 4 show that the model fits the sectoral choices and average income over the life cycle very well. Table A.5 in Appendix B shows that we also fit well the overall variance of income in each sector. Importantly for our small-firm effect question, the model captures well the percentage of individuals who enter self-employment from small and large firms (Table 4). Additional measures of fit are provided in Appendix B.

[14] Forty-one is the highest age recorded among individuals that we observe from the beginning of their labor market careers.

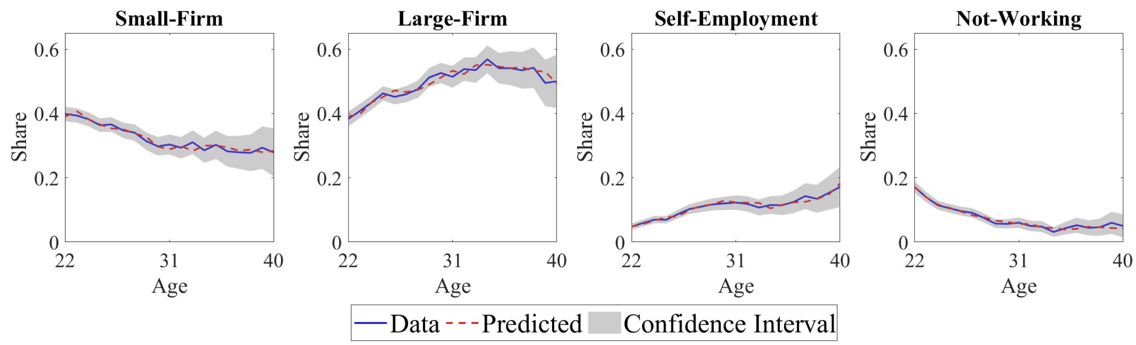


Figure 3: Model Fit - Sector Choices Over the Life Cycle

Notes: Shaded area corresponds to the 95% confidence interval around the data. Simulation of choices at t takes as given the empirical state at t.

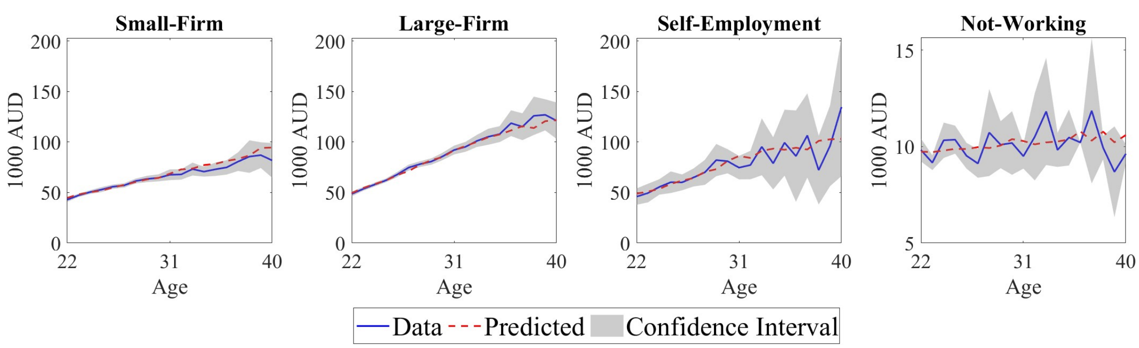


Figure 4: Model Fit - Annualized Income Over the Life Cycle

Notes: Shaded area corresponds to the 95% confidence interval around the data. Simulation of income at t takes as given the empirical state at t and uses the last observed belief in the sample as the best estimate of individual sector ability. Not-working income statistics are conditional on receiving positive not-working income.

Table 4: Model Fit - Transition Matrix

	Data				*Simulation*			
	Self-Employment	Small-Firm	Large-Firm	Not-Working	Self-Employment	Small-Firm	Large-Firm	Not-Working
Self-Employment	80.2	11.4	5.6	2.8	81.1	10.6	5.4	2.9
Small Firm	4.6	76.8	14.2	4.3	4.6	76.7	14	4.8
Large Firm	1.4	9.2	86.7	2.7	1.5	9.3	86.1	3.2
Not-Working	3.8	19.8	16.8	59.7	3.1	17.1	18	61.8

Notes: Previous choices are shown in the rows, current choices are shown in the columns.

5 Structural Estimates

In this section we discuss the estimates of the main pieces of the model, relegating to Appendix C all remaining parameter estimates. Our discussion focuses on the profiles of returns to own- and cross-sector experience, the scope and speed of learning, the presence of correlated learning, the impact of initial wealth, the switching costs of transitioning into and out of self-employment, and the effect of father's background on the non-pecuniary benefits from being self-employed.

Returns to own- and cross-sector experience. One of the main economic mechanisms in our model is learning-by-doing, which is captured by the returns to sector experience. Importantly, in our setup returns can result from experience accumulated in the same sector (*own-sector returns*) or in other sector (*cross-sector returns*). Figure 5 shows our estimated profiles of own-sector returns to experience. The small-firm sector has the flattest profile and the large-firm sector has the steepest. For individuals with five years of experience the own-sector returns in large firms (615 AUD/week) already dominate the own-sector returns in small firms or in self-employment; however, small-firm returns still dominate self-employment returns (288 vs 199 AUD/week). After the five-year mark the flatness of the small-firm profile continues and self-employment starts to offer higher returns than the small-firm sector. The steepness of the large-firm own-sector returns increases the opportunity costs of trying self-employment for large-firm workers relative to small-firm workers who, given the flatness of their profile, may find it more attractive to try self-employment to find out whether they are high-achieving entrepreneurs.

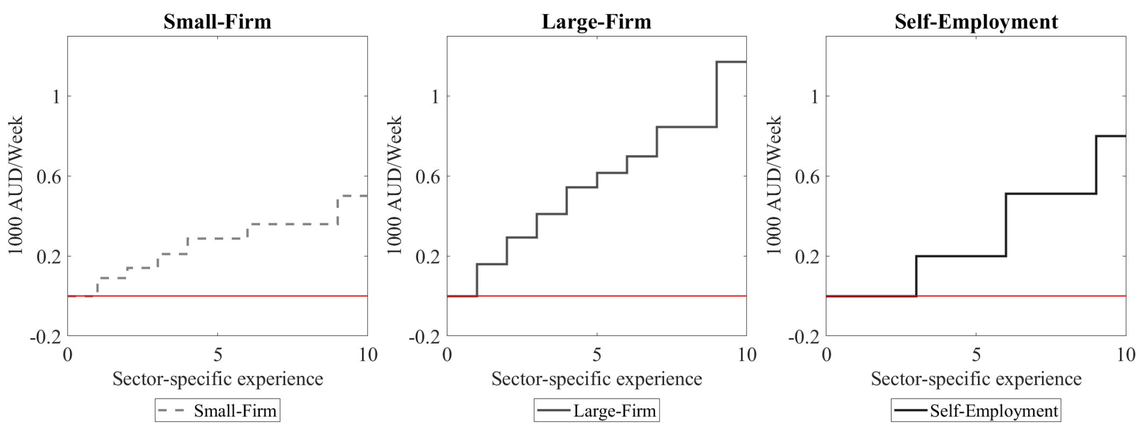


Figure 5: Own-Sector Returns to Experience

Notes: Returns implied by estimates of the income equation in (2), specified using step functions. See estimates in Table A.6 in Appendix C.

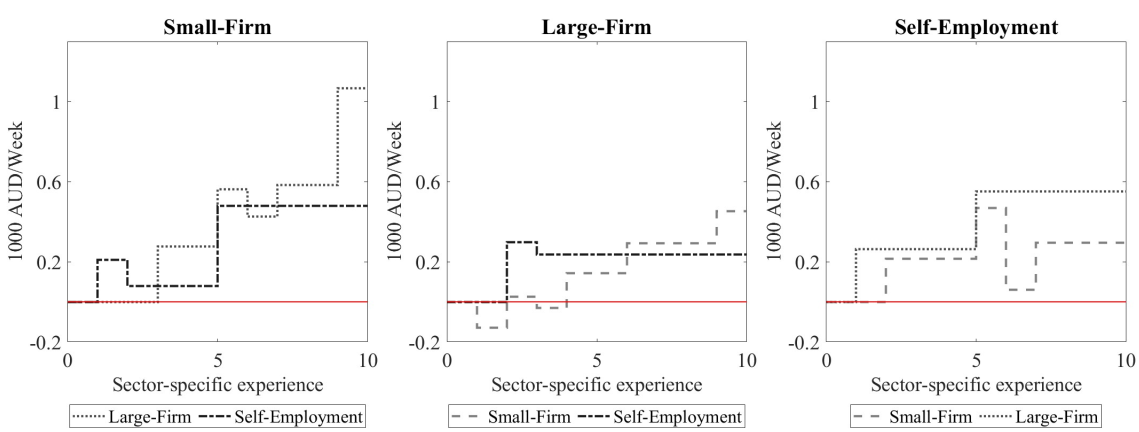


Figure 6: Cross-Sector Returns to Experience

Notes: Returns implied by estimates of the income equation in (2), specified using step functions. See estimates in Table A.6 in Appendix C.

Figure 6 shows our estimated profiles of cross-sector returns to experience. The statistical significance of these profiles (Table A.6 in Appendix C) implies that individuals can carry human capital accumulated in the pay-employment sector over to the self-employment sector (and vice versa). Unsurprisingly, the cross-sector profiles are, for the most part, flatter than the own-sector profiles in Figure 5. However, these returns display important differences. For low levels of cross-sector experience, experience from both paid-employment sectors have similar cross-sector returns in self-employment. After accumulating at least five years of cross-sector experience, large-firm experience seems more valuable in self-employment (right panel in Figure 6). This result rather contradicts what the uncorrected estimates in Figure 2(b) suggested, highlighting the importance of correcting for selection on ability to capture unbiased estimates of the returns to small-firm experience on self-employment and to understand the reasons for the higher rate of transition into entrepreneurship from small firms.[15]

Going in the opposite direction, cross-sector returns to self-employment experience seem higher in small firms (left and middle panels in Figure 6). Since former small-firm workers tend to come back to the small-firm sector after a spell of self-employment, these profiles can help explain why small-firm workers are more likely to embark upon self-employment than large-firm workers.[16] Finally, an important feature revealed by Figure 6 is the versatility of human capital accumulated in large firms. The cross-sector returns to large-firm experience (Figure 6) rival the own-sector returns in self-employment at low levels of experience, and dominate the own-sector returns in small firms at high levels of experience (Figure 5).

Learning about sector-specific ability. Since individuals' unobserved, sector-specific ability affects their income, the learning process is determined by two components: the variance of sector-specific ability in the population and the variance of the idiosyncratic income shocks. Our estimates of both these components are presented in Table 5. Consistent with results in Hincapié (2020), two features are noticeable regarding the variance of sector ability in the population. First, there is a clear ranking in the scope for learning (the magnitude of the variance) across sectors, with self-employment at the top and the small-firm sector at the bottom. Second, there is also a clear ranking in the scope for learning across education levels with high-education individuals having a greater scope for learning in all sectors. For example, in the self-employment sector, a standard deviation in ability corresponds to an increase in income of 1,353 AUD/week (659 AUD/week) for individuals with college or more (less than college); at the opposite end, in the small-firm sector a standard deviation in ability corresponds to an increase of 490 AUD/week (425 AUD/week) for

[15] In a separate exercise we estimated the income equations using OLS and confirmed that the cross-sector returns from small-firm experience on self-employment do shrink once we correct for selection.

[16] For former small-firm (large-firm) workers who are currently self-employed, the probability of going back to the small-firm (large-firm) sector conditional on exit is 0.72 (0.42) .

individuals with college or more (less than college).[17] These numbers indicate that those with college or more have the most to gain from learning their position in the self-employment ability distribution.

Table 5: Sector Ability Distribution and Idiosyncratic Variance

Variance-Covariance Matrix of Sector Ability Δ

	Less than College						*College or More*					
	Self-Employment		Small-Firm		Large-Firm		Self-Employment		Small-Firm		Large-Firm	
	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se
Self-Employment	0.435	0.038					1.831	0.225				
Small-Firm	0.178	0.015	0.181	0.016			0.406	0.063	0.240	0.024		
Large-Firm	0.211	0.015	0.141	0.008	0.221	0.005	0.544	0.054	0.225	0.011	0.467	0.037

Variance of Idiosyncratic Income Shocks σ_j^2

	Less than College						*College or More*					
	Self-Employment		Small-Firm		Large-Firm		Self-Employment		Small-Firm		Large-Firm	
	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se
Variance	0.854	0.033	0.175	0.009	0.227	0.009	3.314	0.564	0.317	0.030	0.851	0.051

Notes: This table includes point estimates (coeff) and standard errors (se) corrected for two-stage estimation using subsampling estimation over 100 subsamples without replacement.

The significance of the off-diagonal terms of the variance-covariance matrix of sector ability indicates that the sector abilities are correlated. Figure 7 summarizes the correlations implied by the parameters in the top panel of Table 5. For both education levels the correlation is the highest between paid-employment sectors, between 3 and 14 percent higher than the correlation in ability between self-employment and any of the paid-employment sectors. For high-education (low-education) individuals self-employment ability is more correlated with small-firm (large-firm) ability. All correlations are higher for low-education individuals but their scope for learning is smaller, perhaps suggesting a lower diversity in ability.

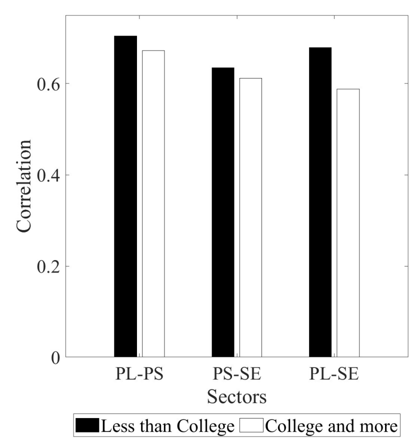


Figure 7: Implied Correlation Between Abilities

Notes: Correlation between sector abilities per education level implied by the estimates in Table 5. "PS", "PL", and "SE" stand for small-firm, large-firm, and self-employment, respectively.

[17] Ability is measured in 1,000 AUD/week.

A direct consequence of these correlations is that the learning process is also correlated; in other words, income signals received in one sector decrease the uncertainty regarding the ability in another. The speed of this learning process as well as the extent of correlated learning critically depends on the variance of the idiosyncratic income shocks in the bottom panel of Table 5. Income signals from sectors with high idiosyncratic variance will be less informative if much of the residual variation is due to unexplained factors captured by the idiosyncratic shocks (e.g. luck) rather than ability. Figure 8 illustrates the speed of learning by plotting the share of initial uncertainty about self-employment ability that is eliminated after five years of experience in each of the sectors.[18] For both education levels self-employment experience is the best source for reducing uncertainty about self-employment ability and the speed of learning from own-sector signals is very similar: more than 70 percent of the uncertainty is eliminated after five years of self-employment experience. The similarity in learning speeds across education levels results from high-education individuals having both a higher scope for learning about self-employment ability (1.831 vs 0.435) and higher idiosyncratic self-employment income variance (3.314 vs 0.854). Both small- and large-firm income signals have similar information content regarding self-employment ability: between 28 and 38 percent of the uncertainty about self-employment ability is eliminated after five years of paid-employment experience.

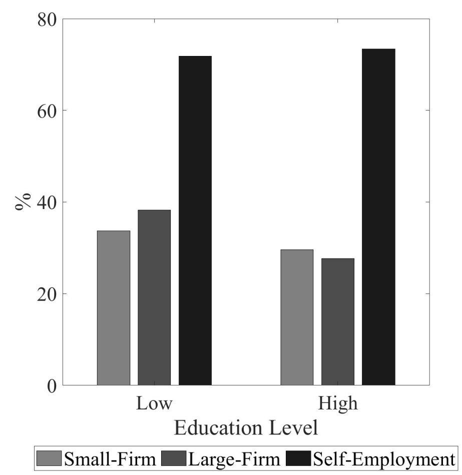


Figure 8: Prior Variance Eliminated after Five Years of Sector-Specific Experience

Notes: The figure shows the percentage of prior (belief) variance regarding self-employment ability eliminated after accumulating five years of experience in sector j and zero in any other sector. For example, for high-education people, the small-firm bar shows that around 40 percent of the prior variance in self-employment ability is eliminated after five years of small-firm experience and zero years of experience in large-firm and self-employment.

The switching costs and benefits of transitioning in and out of self-employment. Switching costs capturing non-pecuniary motivations can also explain why small-firm workers are more likely to transition into self-employment or why the self-employed are more likely to transition into the

[18] This exercise holds constant the experience in other sectors at zero.

small-firm sector.[19] To obtain the monetary value of the estimated switching costs and benefits, we divide them by the marginal utility of annual income.[20] Given the persistence observed in sector choices (Table 3), it is not surprising that individuals draw the most benefits from staying in the same sector (diagonal terms in Table 6). More notable is the fact that, although both paid-employment sectors are at least as persistent as self-employment (Table 3), it is the self-employed who obtain the highest benefits from staying in the sector, with a monetary equivalent (155,700 AUD) that is about twice what paid-employees obtain. This result is consistent with a higher willingness of self-employed individuals to sacrifice earnings in exchange for the non-pecuniary benefits of being self-employed (Hamilton, 2000).

Small-firm workers, who are three times as likely as large-firm workers to switch into self-employment (Table 3), draw switching benefits that are twice the size (in absolute value) of the switching costs large-firm workers face from the transition, suggesting that switching cost and benefits likely play an important role explaining the flow of small-firm workers into self-employment. Large-firm workers appear to be particular "reluctant" entrepreneurs, experiencing switching costs when starting a business, despite the relatively high return to large-firm experience in self-employment shown in Figure 6. Given that about two thirds of transitions from small-firm (large-firm) work into self-employment are within (out-of) industry (Table A.2, Appendix A.2), the flatter profile of cross-sector returns in self-employment for small-firm experience (Figure 6) suggests that the higher transition rate from the small-firm sector is likely due to industry preferences reflected in the switching costs and benefits rather than returns to industry-specific human capital. For individuals transitioning out of self-employment something similar happens. Self-employed individuals transitioning into the large-firm sector face switching costs that are about three times the size (in absolute value) of the switching benefits that those who transition into the small-firm sector obtain. This result is consistent with self-employed individuals, who may have accustomed to being their own bosses, not preferring to switch into large firms with greater reliance on rules and less freedom of action (Brown and Medoff, 1989).[21]

Fathers' characteristics. Fathers' sector and occupation have been found to have an effect on their offsprings' self-employment participation and outcomes (Hundley, 2006). Similar to those

[19]The full set of utility parameters can be found in Table A.8 in Appendix C.

[20]The marginal utility of annual income y_a is $\frac{\partial u}{\partial y_a} = \rho \alpha_y \exp\{-\rho y_a\}$. The point estimates for ρ and α_y are 0.508 and 6.186, respectively. Since annual income is measured in 100,000 AUD, the marginal utility of income evaluated at the median annual income for working individuals in the sample (59,000 AUD) is 2.33. Hence, the monetary value of one utility unit is about 43,000 AUD ($\approx$100,000/2.33). Both ρ and α_y are statistically significant at the 99% level (Table A.8 in Appendix C). Dividing our CARA parameter by 100,000 for comparison, shows that our estimate (scaled value of 5.08E-06) is between values found in the literature (see Table A.6 in Hincapié (2020)).

[21]In addition, Table A.4 in Appendix A.2 implies that the presence of children at home may also affect the transition preferences captured by the switching costs and benefits. Relative to individuals with children at home, individuals with no children at home are more likely to switch into self-employment from the small-firm sector and vice versa.

Table 6: Monetary Value of Estimated Switching Costs and Benefits

	Self-Employment	Small-Firm	Large-Firm	Not-Working
Self-Employment	155.7	5.8	-26.1	
Small Firm	21.1	75.7	3.4	
Large Firm	-16.9	-0.7	83.3	
Not-Working				87.1

Notes: Matrix element (i, j) represents the benefits of choosing sector in column j at t given that the sector in row i was chosen at $t-1$. Monetary values are calculated at the median annual income for working individuals in the sample (59,000 AUD) and reported in 1,000 AUD.

results, we find that the non-pecuniary benefits of self-employment are more affected by father's occupation than father's education (Figure 9).[22] Consistent with results in Hout and Rosen (2000), we find that the non-pecuniary benefits of self-employment are higher for individuals with white-collar working fathers (relative to blue-collar). Moreover, the non-pecuniary gain from having a white-collar working father is more than twice in self-employment than in paid-employment sectors, suggesting that father's occupation plays a stronger role in shaping entrepreneurial preferences than paid-employment ones.

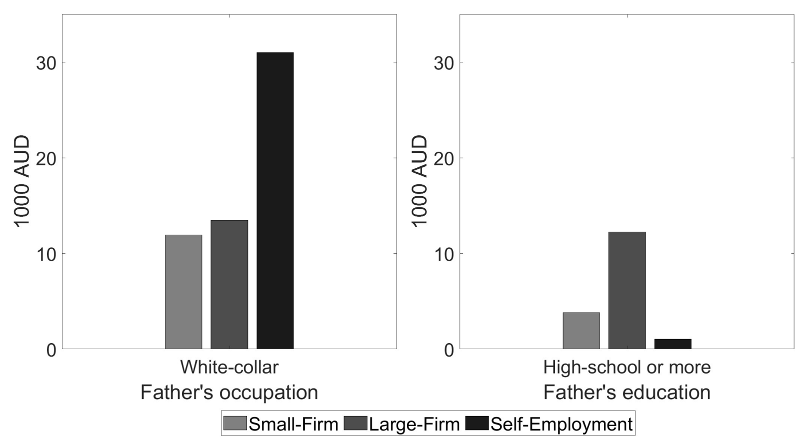


Figure 9: Monetary Equivalent of Father's Background Non-Pecuniary Benefits
Notes: Monetary values of the contribution to non-pecuniary sector benefits from father's occupation and education. See Table A.8 in Appendix C. The baseline group for father's occupation is blue collar occupation. The baseline group for father's education is less than high school. Monetary values are calculated at the median annual income for working individuals in the sample (59,000 AUD) and reported in 1,000 AUD.

Initial wealth. Both a person's income and their non-pecuniary benefits from working in a sector are affected by their initial wealth. Results in Appendix Table A.6 indicate that the marginal effect of initial wealth on self-employment income is between three and four times as large as on paid-employment income. Going from the 25th to the 75th percentile of initial wealth increases weakly self-employment income by 18.6 percent (321 AUD), large-firm income by 7.3 percent (124 AUD), and small-firm income by 5.7 percent (77 AUD). The marginal impact of initial wealth on non-

[22]Since we split fathers between those with less than high school and those with high school or more, we cannot rule out whether there exist stronger effects of education at the highest levels of parental education.

Table 7: Self-Employment Life Cycle Descriptives by Initial Wealth and Education

	Initial Wealth		*Education*	
	Bottom Quartile	Top Quartile	Less than College	College or More
Tried by age 40 (%)	37	41	42	34
Present value of income if tried by age 40	773	914	787	1,036
Overall rate of entrepreneurship (%)	10.0	12.7	12.0	10.9
Entry				
Transition rate from small firms (%)	4.2	4.8	4.7	4.1
Transition rate from large firms (%)	1.4	1.5	1.5	1.3
Ratio of entry transition rates	3.1	3.2	3.1	3.3
Ability at 1st entry from small firms	91	145	46	354
Ability at 1st entry from large firms	113	191	64	420
Exit				
Overall exit rate from entrepreneurship (%)	17.7	14.9	16.8	13.3
Transition rate into small firms (%)	9.5	8.3	9.4	7.3
Transition rate into large firms (%)	4.9	4.5	4.7	4.5
Ratio of exit transition rates	1.9	1.9	2.0	1.6

Notes: Present value of income (PVI) is reported in 1000 AUD.

pecuniary benefits follows a different ordering: it is the highest in the large-firm sector and smallest in self-employment (Table A.8). These results suggest that initial wealth impacts self-employment decisions more strongly through its effect on the performance of the business, perhaps preventing it from reaching its optimal scale as in Evans and Jovanovic (1989), than through shaping the preferences of entrepreneurs.

To focus our attention on the role of initial wealth on the small-firm effect, we use our estimated model to simulate the life-cycle self-employment behavior of individuals at the bottom and top quartiles of the distribution of initial wealth. Table 7 shows general descriptives of this simulation. The impact of the income mechanism of initial wealth is apparent on the present value of income for individuals at the top quartile.[23] This results in a higher rate of experimentation with self-employment and a lower exit rate for these individuals. However, the differences in the rates of entry into and exit from self-employment between workers in the paid-employment sectors are virtually identical at both ends of the distribution of initial wealth, suggesting that the small-firm effect is not explained by differences in initial resources.

Education. Previous literature has identified college education as a driver of entrepreneurial innovation (Ehrlich et al., 2017). Consistent with this literature, our results suggest that individuals with college or more have both a higher level of entrepreneurial returns (Table A.6 in Appendix

[23] In a separate counterfactual in Appendix C.3 we evaluate the impact of unemployment income on life cycle self-employment choices. Results indicate that cutting unemployment benefits by half slightly reduces the average quality of those entering self-employment. However, the life cycle present value of income of those who try self-employment does not decrease due to an overall decrease in the share of not-working.

C) and a higher scope of possible outcomes as measured by the variance of self-employment ability (Table 5). To further understand the role of education on life cycle self-employment behavior we have summarized our baseline simulations by education level in Table 7. While the share of those who try self-employment is 8 percentage points higher for individuals with less than college, the self-employment ability of entrepreneurs with college of more is substantially higher, between 6.5 and 7.7 times higher. This wide gap in self-employment ability is consistent with college educated individuals driving entrepreneurial innovation and it also explains their lower exit rate from entrepreneurship. While education is associated with entrepreneurial success, the patterns of entry and exit into self-employment from small and large firms are very similar for college and non-college graduates, suggesting that the small-firm effect is not primarily driven by educational differences across sectors.

6 The Mechanisms of the Small-Firm Effect

In order to assess how learning-by-doing, learning-about-ability, and non-pecuniary motivations affect self-employment dynamics we undertake five counterfactual decompositions. The first two decompose the role of learning by focusing on human capital accumulation. One of them decomposes the effect of own-sector returns by replacing a subset of parameters of the small-firm weekly income process (the coefficients on education, initial wealth, own-sector experience, and the constant), with those from the large-firm weekly income process.[24] Under this decomposition the only difference between the income processes of small- and large-firm workers is the cross-sector returns. The other learning-by-doing decomposition focuses on cross-sector returns between paid-employment and self-employment. In this decomposition self-employment experience has the same returns in both paid-employment sectors and, conversely, both paid-employment sectors have the same returns in the self-employment sector. In practice we replace the small-firm cross-sector return profiles with their large-firm counterparts.[25]

The next two counterfactuals decompose the role of learning-about-ability focusing on the accumulation of information about sector-specific ability. First, we allow individuals to have full information about their sector-specific ability. To separate the effect of sorting on ability from a reduction in income risk (also caused by learning) we augment the idiosyncratic variation in income

[24] In other words, we replace the point estimates of education, own-sector experience, initial wealth, and the constant in the *Small-Firm* column of Table A.6 in Appendix C with those in the *Large-Firm* column.

[25] To implement this counterfactual we use our estimates in Table A.6 in Appendix C. We replace the profile of cross-returns to self-employment experience in the *Small-Firm* column with the profile of cross-returns to self-employment experience in the *Large-Firm* column. In addition, we replace the profile of cross-returns to small-firm experience in the *Self-Employment* column with the profile of cross-returns to large-firm experience also in the *Self-Employment* column.

to keep the income risk constant at the initial baseline level.[26] Second, we eliminate correlated learning. We do this by diagonalizing the population distribution of ability in the individuals' belief formation process. Hence, while the underlying ability distribution is kept the same as in the baseline, individuals' income signals in one sector are not used to update beliefs regarding their ability in other sectors. In this way we separate information spillovers from the correlation in ability.

We also assess the role of switching costs and benefits associated with transitions between paid and self-employment. To do this we equalize the switching costs and benefits of transitioning into self-employment from either paid-employment sector and we also equalize the switching costs and benefits of transitioning out of self-employment into either paid-employment sector. In practice we replace the small-firm non pecuniary switching costs and benefits with their large-firm counterparts.[27]

To analyze behavior under each counterfactual regime we replicate the initial (3,098) individuals in the estimation sample 100 times and simulate their behavior forward under the baseline and under each of the counterfactual regimes. Their ability vectors are drawn from the estimated distribution of ability and kept constant across counterfactuals.

Self-employment participation and income. Overall, self-employment experimentation (as measured by the share of individuals who tried it by age 40) and the overall rate of entrepreneurship are most affected by learning by doing and transition preferences. On the one hand, Table 8 suggests that if the own-returns in the small-firm sector were as steep as in the large-firm sector (Table A.6), or the preferences for transitioning into entrepreneurship as low (Table A.8), self-employment experimentation would decrease by 53 and 38 percent (from 40 to 19 and 25 percent), respectively. On the other, if the cross-returns to small-firm experience in entrepreneurship were as high as the cross-returns to large-firm experience, experimentation would increase by 45 percent (from 40 to 58 percent). While the effects of these counterfactuals on the overall rate of self-employment go in the same direction, the results become even stronger for learning by doing. While equalizing own-returns cuts the rate of self-employment by 77 percent (from 11.8 to 2.7 percent), equalizing cross-returns almost doubles it (from 11.8 to 20.5 percent).

The life-cycle income of those who try self-employment is most affected by information frictions and own-returns. Eliminating uncertainty about sector-specific ability enhances sorting in-

[26] We achieve this by augmenting the sector-specific idiosyncratic variance. Concretely, in this counterfactual the sector-specific idiosyncratic variance is equal to the estimated sector-specific idiosyncratic variance plus the variance of ability in the population.

[27] We replace the point estimate for *Small-Firm at* $t-1$ (0.491) with the point estimate for *Large-Firm at* $t-1$ (-0.393) in the *Self-Employment* column of Table A.8 in Appendix C; and we also replace the point estimate for *Self-Employment at* $t-1$ in the *Small-Firm* column (0.135) with the point estimate for *Self-Employment at* $t-1$ in the *Large-Firm* column (-0.609).

Table 8: Self-Employment Life Cycle Behavior Under Counterfactual Regimes

	Baseline	*Learning-By-Doing*		*Learning-About-Ability*		*Preferences*
		Own Returns	Cross Returns	Full Information	Uncorrelated Learning	Equal Transition Benefits
Tried by age 40 (%)	40	19	58	41	41	25
Present value of income if tried by age 40	833	991	841	887	710	830
Overall rate of entrepreneurship (%)	11.8	2.7	20.5	12.9	11.3	7.2
Entry						
Transition rate from small firms (%)	4.6	1.1	7.0	4.6	4.5	1.7
Transition rate from large firms (%)	1.5	1.1	2.6	1.6	1.4	1.2
Ratio of entry transition rates	3.1	1.0	2.7	2.9	3.2	1.4
Ability at 1st entry from small firms	103	164	90	306	-208	113
Ability at 1st entry from large firms	140	196	139	388	-211	142
Exit						
Overall exit rate from entrepreneurship (%)	16.1	37.4	10.9	14.1	16.8	15
Transition rate into small firms (%)	9.0	31.4	6.4	7.8	9.5	5.3
Transition rate into large firms (%)	4.7	3.8	2.7	3.7	4.7	6.4
Ratio of exit transition rates	1.9	8.3	2.4	2.1	2.0	0.8

Notes: Present value of income (PVI) is reported in 1000 AUD. Ability is reported in AUD per week; in other words, its contribution to weekly self-employment income. Columns: *Own Returns* equalizes the own-sector returns of small and large firms; *Cross Returns* equalizes the cross-sector returns of small and large firms; *Full Information* eliminates information frictions; *Uncorrelated Learning* eliminates correlated learning; *Equal Transition Benefits* equalizes the switching costs and benefits of transitioning into and out of self-employment across both paid-employment sectors.

creasing the present value of income (PVI) by 6 percent (from 833 to 887 thousand AUD). Conversely, eliminating learning spillovers across sectors hinders sorting decreasing the PVI by 15 percent (from 833 to 710 thousand AUD). Additionally, equalizing own-returns to paid-employment experience increases the PVI by 19 percent (from 833 to 991 thousand AUD). This happens because under this counterfactual self-employed individuals coming from and transitioning into the small-firm sector, the most common routes in and out of self-employment, now enjoy steeper own-returns profiles.

Entry margin. Table 8 shows that the transition rate from paid employment into self-employment is most affected by own-sector returns and preferences. If own-sector returns in small firms were as steep as those in large firms the transition rate into self-employment from small firms would decline by 76 percent (from 4.6 to 1.1 percent). Coupled with a much weaker effect on the transition rate from large firms, this counterfactual erases the gap in transition rates into self-employment between both paid-employment sectors. Equalizing transition preferences has a similar but weaker effect as it does not entirely eliminates the small-firm effect at the entry margin; under this counterfactual the ratio of transition rates goes from 3.1 in the baseline to 1.4.

Table 8 also shows that the quality of those who enter self-employment is most affected by information frictions and own-sector returns. Highlighting the impact of imperfect information, we find that the ability of first entrants into self-employment almost triples (from 103 to 306 AUD per week) when individuals are allowed to sort on ability instead of beliefs. Importantly, the negative impact of imperfect information on quality is substantially reduced by information spill-overs; when we prevent individuals from using signals from other sectors to update their beliefs about self-employment ability the ability of first entrants declines dramatically (from 103 to -208 AUD per week). Similar effects hold for entrants from large firms. Finally, if own-sector returns in small firms were as steep as those in large firms, first entrants from small firms would get proportionally better than entrants from large firms (a 59 percent increase for entrants from small firms versus a 40 percent increase for entrants from large firms). This result reflects the increase in the opportunity cost for small-firm entrants as their profile of own returns is now better. However, entrants from large firms continue to be better due to their weaker switching benefits from transitioning into self-employment.

Exit margin. Our baseline simulation in Table 8 reproduces the stylized fact that individuals exiting from self-employment transition into small firms about twice as often as they transition into large firms (Table 3). Consistent with our results at the entry margin, the exit margin is most affected by learning by doing and preferences. If own-sector returns in small firms were as steep as those in large firms, the exit rate from self-employment would more than double (from 16.1 to 37.4 percent). This change in small-firm returns, which improves the outside option for the self-employed, dramatically increases the small-firm effect at the exit margin. The ratio of exit rates from self-employment (exit into small firms over exit into large firms) increases by more than four times (from 1.9 to 8.3). A much milder increase of 26 percent in the ratio (1.9 to 2.4) occurs when the cross-sector returns to small-firm experience are equalized to those of large-firm experience. Finally, equalizing transition preferences across paid-employment sectors, which weakens the pull into small-firms out of self-employment almost eliminates the disparity in exit rates bringing the ratio of exit rates down from 1.9 to 0.8. Together, these results suggest that the small-firm effect at the exit margin is mostly due to own-sector returns and preferences, these two forces modulate the differential value of the small-firm sector as a more attractive outside alternative from self-employment.

7 Conclusion

Are small firms "hothouses" for entrepreneurship that disproportionately spawn highly successful startups? The results from this paper indicate the answer is no. After estimating a dynamic structural model of self-employment choice using panel data from Australia covering 2001-2019, we conclude that the widely observed "small-firm effect" reflects two main factors. First, human capital acquired in small firms offers less returns, reducing the opportunity costs of small-firm workers becoming entrepreneurs (the learning-by-doing effect). As a result, self-employment entrants from smaller firms tend to be less able entrepreneurs, on average, than those entering from large firms. Second, individuals sort between small firms and entrepreneurship based on similarities of the non-pecuniary benefits and switching costs associated with each sector. This is consistent with the idea that small firms and self-employment offer similar levels of job autonomy and task variety that individuals find appealing. At the exit margin, we find that differences in the cross-sector versatility of human capital, in other words, the returns on a given sector from experience accumulated in another, together with preferences, can help explain why the self-employed tend to exit more into small firms. We also find that large-firm experience is more valuable in self-employment. Finally, our results indicate that both small and large firms provide similar opportunities for workers to learn about their entrepreneurial abilities, which rules out learning-about-ability as an explanation for the small-firm effect. Unlike most prior studies, we allow abilities to be correlated across sectors, and show that high (low) ability large- and small-firm employees tend to be high (low) income entrepreneurs.

Our findings have important implications for policies aimed at promoting the entry and growth of high-potential entrepreneurs, and point at potential inefficiencies existent in local systems that aim to foster economic growth through small firms' impact on subsequent entrepreneurship (Glaeser et al., 2015). While small-firm employees have a stronger preference for entrepreneurship, they tend to open low earning businesses. By contrast, large-firm workers have human capital that is more transferrable to entrepreneurship, and these individuals open businesses with greater income potential. However, these workers also tend to be the most "reluctant" entrepreneurs due to their more attractive profile of returns to experience and their relatively large switching costs of transitioning to self-employment. Policies promoting entrepreneurship have generally focused on reducing capital constraints by providing grants, loans, or subsidized access to financing. We indeed find that individuals with greater initial wealth open higher income businesses: moving from the bottom to the top quartile of wealth increases self-employment weekly income by 321 AUD. On the other hand, we estimate that 5 years of large firm experience increases weekly entrepreneurial income by 551 AUD. Consequently, an alternative to providing subsidized startup capital might be a policy targeting large-firm workers in an effort to encourage high growth business entry among these reluctant, but potentially highly-productive, entrepreneurs.

A Data Appendix

The Household, Income and Labour Dynamics in Australia (HILDA) survey, launched in 2001, is a nationally representative household-based panel study that follows more than 17,000 Australians each year. Our sample is restricted to men and it spans years 2001 through 2019. Below we describe our main variables.

Years of education. We collapse the Australian Qualifications Framework into two categories of completed education: college and above (master or doctorate, grad diploma, bachelor) and less than college (diploma, certificate III/IV, high school or less).

Sector. We classify as *employed* at t individuals who at any time during the last 7 days did any work in a job, business or farm. We classify as *not-working* at t individuals who were not employed at any time during the last 7 days or who were employed without pay in a family business. We classify as *self-employed* at t individuals who declared that they worked in their own businesses with or without employees and that the business is their main job (if they have more than one job).

Firm size. For salaried workers, firm size is coded as follows. First we obtain the number of employees at the firm. If the employer operates at only one location in Australia, this number is determined by the employees at that location. If the employer operates at more than one location, this number is determined by the employees at all locations throughout Australia. Then, we define a worker to be in the *small-firm* sector if the firm they are currently working for has less than 100 employees, and in the *large-firm* sector if the firm has 100 employees or more.

Government support. Our measures of income for individuals not working correspond to the Newstart and Youth Allowances. Newstart is the main unemployment benefit paid to eligible job-seekers, ages 22 to 64, with permanent residency in Australia. The Youth Allowance is a benefit paid to eligible individuals ages 16 to 24 with permanent residency in Australia.

Working weeks. HILDA computes the percent of time spent in all jobs during the last financial year. We use this variable to obtain the number of weeks an individual worked.

Not-working income weeks. This is defined as the number of weeks an individual received Newstart or Youth allowances during the last financial year.

Weekly income. For working individuals our measure of income is constructed as follows. First we compute the sum of their gross wage/salary, profit from unincorporated businesses, and the dividends from incorporated businesses from the last financial year. Then we divide this annual income by the number of working weeks. This measure is similar to the one used in Hessels et al. (2020).[28]

For not-working individuals we first compute the sum of Newstart and Youth Allowance pay-

[28] HILDA also collects the most recent weekly/biweekly pay; however, most business owners report not receiving any income. Hence, we think the annual measure captures income better, especially for the self-employed.

ments in the last financial year. Then we divide this amount by the number of not-working income weeks. If an individual does not know the annual amount, HILDA collects the fortnight amount, which we divide by two to obtain their weekly not-working income.

Initial wealth. HILDA collects household wealth information every four years (waves 2, 6, 10, 14, and 18). We use the household net worth variable to define wealth at the beginning of the labor market career. Initial wealth for a person who enters the labor market at age t is defined as the closest household net worth at age $t' \leq t$; this covers 65.1 percent of all individuals (65.0 percent of individual-year observations). If missing, we defined initial wealth as the closet wealth in the next survey wave, within four years of entering the labor market; this covers 22.4 percent of all individuals (31.1 percent of individual-year observations). For the remaining observations we impute initial wealth using a linear regression of initial wealth on net home value, an indicator of home ownership, age, age^2, and education; this covers the remaining 12.5 percent of individuals (3.9 percent of individual-year observations). Since initial wealth is a right-skewed variable that includes zero and negative values we use the inverse hyperbolic sine transformation (e.g. Friedline et al. (2015) and Pence (2006)) of initial wealth in order to flexibly accommodate its effect on sector choices. If initial wealth is denoted generically by z, its inverse hyperbolic sine transformation $\tilde{z}$ is given by

$$\tilde{z} = log\left(z + \sqrt{z^2+1}\right) \tag{A.1}$$

Father's occupation. This corresponds to the father's occupation when the respondent was age 14. We define three categories: blue collar (community and personal service workers, sales workers, machinery operators, drivers, and laborers), white collar (managers, professionals, technicians, trades workers, and clerical and administrative workers), and missing (never worked, no father, or don't know).

Father's education. This corresponds to the father's completed education. We define three categories: less than high school, high school or more, and missing.

A.1 Final Sample

To construct our final sample we define the beginning of an individual's career and address gaps in data undertaking some imputations as follows.

Beginning of an individual's labor market career. We determine the beginning of an individual's labor market career using potential experience. Let $\tilde{x}$ denote potential experience. For robustness we use two different measures. Let a first measure of potential experience be defined as:[29]

$$\tilde{x}_0^1 \equiv Age_0 - \max\{\textit{Years of education}, 16\} - 6 \tag{A.2}$$

[29] A similar measure is used in Hincapié (2020) and Todd and Zhang (2020).

where the subindex 0 indicates that the measure is taken the first time we observe an individual at an age greater than or equal to 22 and after leaving full-time education. Since this first measure does not account for years not working and for differences between years of certified education and the number of years an individual might have actually spent at school, we complement our measure with a second measure of potential experience. Let the maximum possible age of entry to the labor market, denoted $\overline{Age}_0$, be defined as:

$$\overline{Age}_0 = Age_0 - Exp_0 \tag{A.3}$$

where Exp_0 (if observed) indicates labor market experience. Let the (approximate) labor market experience at age 22 be defined as:

$$Exp_{22} = \max\{0, 22 - \overline{Age}_0\} \tag{A.4}$$

and let τ^e be the number of years since the individual left full-time school.[30] Our second measure of potential experience is defined as:

$$\tilde{x}_0^2 \equiv \begin{cases} Exp_0 - Exp_{22} & \text{if } Exp_0 \text{ is observed} \\ \tau_0^e & \text{if } Exp_0 \text{ is missing} \end{cases} \tag{A.5}$$

Finally, to maximize the number of observations in our sample we combine both measures of potential experience by defining:

$$\tilde{x}_0 \equiv \begin{cases} \tilde{x}_0^1 & \text{if only } \tilde{x}_0^1 \text{ is observed} \\ \tilde{x}_0^2 & \text{if only } \tilde{x}_0^2 \text{ is observed} \\ \min\{\tilde{x}_0^1, \tilde{x}_0^2\} & \text{if both are observed} \end{cases} \tag{A.6}$$

We retain in the sample only those individuals for whom $\tilde{x}_0 \leq 3$ and define the start of the individual's labor market career as the period when $\tilde{x}_0$ is calculated.

Imputation. If an individual is missing from the data set at t but he is available in $t-1$ and $t+1$ we impute his data at t to be the same as his data at $t-1$. If an individual is missing from the data set at t and $t+1$ but he is available in $t-1$ and $t+2$ we impute his data at t to be the same as his data at $t-1$ and his data at $t+1$ to be the same as his data at $t+2$. For individuals available at t but with missing variables at t we impute the value of the variable by replacing it with the nearest past

[30]Time since leaving full-time education is a survey variable (EHTSE) asked when individuals are first added to the survey which corresponds to the sum of time in paid-work (EHTJB), time not working (EHTUJ) and time looking for job (EHTO).

or future value available, up to three years ($t-3, t-2, ..., t+2, t+3$). Out of 18,535 observations in our final sample, only five percent have imputed information.

Dropping observations and sample construction. Table A.1 describes the process through which we keep observations in our final sample:

Table A.1: Final Sample Construction

Dropping Condition	Remaining Observations (Individual-Year)	Remaining Individuals
Initial sample	401,342	43,770
Drop women	195,874	21,748
Drop if age < 22	132,628	15,215
Drop years before finishing full-time school	126,186	14,807
Drop remaining years if missing for more than 2 consecutive years	108,653	12,686
Drop if missing education	108,588	12,679
Drop remaining years if missing firm size	107,568	12,608
Drop remaining years if missing income	105,805	12,542
Drop remaining years if severely disabled	94,566	12,154
Drop not observed from start of career (if $\tilde{x}_0 > 3$)	18,571	3,101
Drop income outliers	18,535	3,098

Notes: Individuals who declare a value greater than eight (out of ten) in the disability scale of the HILDA survey are defined as severely disabled (Wilkins and Laß, 2018).

A.2 Further Descriptives

Table A.2: Transitions into Self-employment - Within Industry and Out of Industry

	Same Industry	Different Industry	Total Transitions
From Small-Firm	68.5	31.5	251
From Large-Firm	35.8	64.2	106

Notes: Percent of transitions into self-employment from salaried work in which individuals remain in the same industry or switch industries. Industries correspond to the 19 main industry divisions in the 2006 Australian and New Zealand Standard Industrial Classification (ANZSIC).

Table A.3: Same-Occupation Transitions into Self-employment - Healthcare

	High Education	*Low Education*	*Overall*
From Small-Firm	9.0	0	7.0
From Large-Firm	0	3.3	1.2

Notes: Percent of transitions into self-employment from salaried work in which individuals remain within healthcare or legal occupations. Healthcare occupations correspond to the 2-digit codes 25 (Health Professionals) and 41 (Health and Welfare Support Workers) of the Australian and New Zealand Standard Classification of Occupations (ANZSCO).

Table A.4: Transition Matrix by Children in the Home

	Self-Employment	Small-Firm	Large-Firm	Not-Working
Without children at home (67% of the sample)				
Self-Employment	78.0	13.4	5.8	2.8
Small-Firm	5.1	76.3	13.9	4.7
Large-Firm	1.4	8.9	86.8	2.9
Not-Working	2.8	20.5	17.2	59.5
With children at home (33% of the sample)				
Self-Employment	83.4	8.5	5.2	2.9
Small-Firm	3.8	77.8	15.0	3.4
Large-Firm	1.5	9.9	86.4	2.2
Not-Working	6.5	17.8	15.6	60.1

Notes: Matrix element (i, j) represents the percent of people in sector in row i who move into sector in column j between t and $t+1$.

B Estimation Appendix

B.1 The Likelihood

The likelihood function for individual i with education level $s_i \in \{0,1\}$ (less than college, college and above), denoted $\mathcal{L}_i$, can be written as:

$$\begin{aligned}\mathcal{L}_i = & \prod_{t=t_{i0}}^{T_i} \prod_{j=0}^{3} \Pr\left(d_{jit} = 1 \mid z_{it}; \Lambda, \Theta, \Gamma\right)^{d_{jit}} \\ & \times \int_{\mu_i} \left\{ \prod_{t=t_{i0}}^{T_i} \prod_{j=1}^{3} f_{y_j}\left(y_{jit} \mid h_{it}, \mu_{ji}; \Theta\right)^{d_{jit}} \right\} dF_\mu\left(\mu_i; \Delta_{s_i}\right) \\ & \times \prod_{t=t_{i0}}^{T_i} \left\{ \left[1 - q(h_{it}^{\nu}; \Gamma)\right]^{1-\nu_{it}} \times \left[q(h_{it}^{\nu}; \Gamma) \times f_{y_0}\left(y_{0it} \mid h_{it}; \theta_0, \sigma_0\right)\right]^{\nu_{it}} \right\}^{d_{0it}}\end{aligned} \tag{A.7}$$

where the state vector $z_{it} = (h_{it}, d_{it-1}, \mathbf{B}_{it})$. Equation (A.7) captures the joint likelihood of observed sectoral choices (d_{jit}), weekly income (y_{jit}), and the extensive and intensive margins of not-working income (ν_{it}, y_{0it}) over time. In our model, individuals choose sectors based on their state, which includes their beliefs but not their actual ability. Hence, sector choices are independent of ability and the choice probabilities can be pulled out of the integration. Using (A.7) we can write the log-likelihood as

$$\ln \mathcal{L}_i = \ln \mathcal{L}_i^d + \ln \mathcal{L}_i^y + \ln \mathcal{L}_i^{nw} \tag{A.8}$$

where $\ln \mathcal{L}_i^d$ is the log-likelihood of sectoral choices, $\ln \mathcal{L}_i^y$ is the log-likelihood of weekly working income, and $\ln \mathcal{L}_i^{nw}$ is the log-likelihood of the not-working weekly income. Below we explain in more detail the two-stage estimation process with which we maximize the likelihood of the data.

B.2 First Stage

Not-working income. Given that we specified $q_t(h^v_t;\Gamma)$ using a probit model and that and η_{i0t} is standard Normal we can rewrite the not-working log-likelihood as

$$\ln \mathcal{L}^{nw}_i = \sum_{t=t_{i0}}^{T_i} d_{0it}\left\{(1-v_{it})\ln\left(1-\Phi\left(\Gamma' h^v_{it}\right)\right)+v_{it}\left[\ln\Phi\left(\Gamma' h^v_{it}\right)+\ln\left(\frac{1}{\sigma_0}\phi\left(\frac{y_{0it}-f_0(h^0_{it};\theta_0)}{\sigma_0}\right)\right)\right]\right\} \tag{A.9}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the cdf and pdf of a standard Normal distribution, respectively. We maximize $\sum_i \ln \mathcal{L}^{nw}_i$ to estimate Γ, θ_0 and σ_0.

Working income. We use the log-likelihood of weekly income and an EM algorithm to estimate the variance-covariance matrices by education level Δ_s, and the remaining components of Θ, which includes the education-specific variance of the idiosyncratic income shocks denoted σ^2_{sj}. To implement the EM algorithm we first compute the log-likelihood as though the ability vector was observed for every individual:

$$\ln \mathcal{L}^y_i(\mu_i) = \sum_{t=t_{i0}}^{T_i}\sum_{j=1}^{3} d_{jit}\ln f_{y_j}\left(y_{jit}\mid h_{it},\mu_{ji};\Theta\right) \tag{A.10}$$

and then implement the expectation and maximization steps below.

Expectation Step. In this step, we compute the expected value of $\ln \mathcal{L}^y_i$ conditional on the observed data and the m iteration estimates of the parameters $\{\Theta^m,\Delta^m_s\}$. Denote the m iteration of this expectation as $\ln \mathcal{L}^{y,m}_i$. Using Bayes' rule the m iteration distribution of sector ability for individual i is a multivariate Normal with mean $\mathbf{E}^m_i$ and variance $\mathbf{V}^m_i$ given by:[31]

$$\mathbf{V}^m_i = \left((\Delta^m_s)^{-1}+\psi^m_i\right)^{-1} \qquad\qquad \mathbf{E}^m_i = \mathbf{V}^m_i\mathbf{W}^m_i \tag{A.11}$$

where ψ^m_i is a 3×3 diagonal matrix with j^{th} diagonal element ψ^m_{ji}, and $\mathbf{W}^m_i$ is a 3×1 vector with j^{th} element $\mathbf{W}^m_{ji}$ and

$$\psi^m_{ji} = \frac{\sum_{t=t_{i0}}^{T_i} d_{jit}}{(\sigma^m_{sj})^2} \qquad\qquad \mathbf{W}^m_{ji} = \frac{\sum_{t=t_{i0}}^{T_i} d_{jit}\left(y_{jit}-f_j(h^y_{it};\theta^m_j)\right)}{(\sigma^m_{sj})^2} \tag{A.12}$$

[31] See James (2011).

Using the m iteration distribution of sector ability for individual i we obtain $\ln \mathcal{L}_i^{y,m}$ as

$$\ln \mathcal{L}_i^{y,m} = -\sum_{t=t_{i0}}^{T_i} \sum_{j=1}^{3} d_{jit} \left[\frac{1}{2} \ln \left(2\pi\sigma_{sj}^2\right) + \frac{1}{2\sigma_{sj}^2} \left(\mathbf{V}_{ji}^m + \left(y_{jit} - f_j(h_{it}^y;\theta_j) - \mathbf{E}_{ji}^m\right)^2 \right) \right] \tag{A.13}$$

where $\mathbf{V}_{ji}^m$ is the j^{th} diagonal element of $\mathbf{V}_i^m$, and $\mathbf{E}_{ji}^m$ is the j^{th} element of $\mathbf{E}_i^m$.

Maximization Step. In this step we obtain $m+1$ iteration parameters Θ^{m+1} and Δ_s^{m+1} as the solution to:

$$\max_{\{\Theta,\Delta\}} \sum_i \ln \mathcal{L}_i^{y,m} \tag{A.14}$$

Substituting equation (A.13) into (A.14) and computing the FOCs yields:

$$\theta_j^{m+1} = \left(H'W_jH\right)^{-1} H'W_jY_j \tag{A.15}$$

$$\left(\sigma_{sj}^{m+1}\right)^2 = \frac{\sum_{i=1}^{N} \sum_{t=t_{i0}}^{T_i} \mathbf{1}\{education_i = s\} d_{jit} \left(\mathbf{V}_{ji}^m + \left(y_{jit} - f_j(h_{it}^y;\theta_j^m) - \mathbf{E}_{ji}^m \right)^2 \right)}{\sum_{i=1}^{N} \sum_{t=t_{i0}}^{T_i} \mathbf{1}\{education_i = s\} d_{jit}} \tag{A.16}$$

where H is the $[NT \times \#(\theta_j)]$ matrix that stacks all vectors of income-relevant observed characteristics h_{it}^y for all observations $\{i,t\}$, W_j is the $[NT \times NT]$ diagonal matrix with d_{jit} on its diagonal, and Y_j is the $[NT \times 1]$ vector that stacks the values of $y_{jit} - \mathbf{E}_{ji}^m$.

Finally, the population variance-covariance matrix of ability for education level s is updated as:[32]

$$\Delta_s^{m+1} = \frac{1}{N_s} \sum_{i=1}^{N} \sum_{s=1}^{2} \mathbf{1}\{education_i = s\} \left(\mathbf{V}_i^m + \mathbf{E}_i^m \mathbf{E}_i^{m\prime} \right) \tag{A.17}$$

where $N_s = \sum_i \mathbf{1}(education_i = s)$.

Iteration. We repeat the expectation and maximization steps until the following stopping criteria is satisfied:

$$\left\| \sum_{i=1}^{N} \ln \mathcal{L}_i^{y,m+1} - \sum_{i=1}^{N} \ln \mathcal{L}_i^{y,m} \right\| < 10^{-4} \tag{A.18}$$

B.3 Second Stage

In the first stage, we recover consistent estimates of the income parameters, $\hat{\Theta}$, the population variance-covariance matrix of sector ability, $\hat{\Delta}_s$, the not-working income parameters, $\hat{\Gamma}$, and we also obtain consistent estimates of beliefs, $\hat{\mathbf{E}}_{it}$. In the second stage, we substitute these estimates

[32] See Hincapié (2020).

into the sector choices part of the log-likelihood which yields:

$$\ln \mathcal{L}_i^d = \sum_{t=t_{i0}}^{T_i} \sum_{j=0}^{3} d_{jit} \ln \Pr\left(d_{jit} = 1 \mid \hat{z}_{it}; \Lambda, \hat{\Theta}, \hat{\Gamma}\right) \tag{A.19}$$

where $\hat{z}_{it} = (h_{it}, d_{it-1}, \hat{\mathbf{B}}_{it})$, and the conditional choice probabilities are:

$$\Pr\left(d_{jit} = 1 \mid \hat{z}_{it}; \Lambda, \hat{\Theta}, \hat{\Gamma}\right) = \frac{\exp\left\{v_{jit}\left(\hat{z}_{it}\right)\right\}}{\sum_{j'} \exp\left\{v_{j'it}\left(\hat{z}_{it}\right)\right\}} \tag{A.20}$$

We obtain estimates of Λ by maximizing $\sum_{i=1}^{N} \ln \mathcal{L}_i^d$.

B.4 Standard Errors

We use subsampling to compute standard errors. We first draw 100 random subsamples without replacement from the individuals in our data set. Each subsample contains $\tilde{p} = 0.9$ of the total number of individuals in the data set (2,788 individuals). We then calculate the first and second stage parameters from each subsample. This procedure yields 100 vectors of estimates. Finally, we use the following formula to calculate the standard error for a given point estimate $\hat{\theta}$:

$$se(\hat{\theta}) = se(\hat{\theta}_r) \cdot \sqrt{\tilde{p}} \tag{A.21}$$

where $se(\hat{\theta}_r)$ is the standard deviation of the 100 subsampling estimates $\hat{\theta}_r$.

B.5 Model Fit

As mentioned in the main text, Table A.5 shows that we fit very well the mean and the standard deviation of sector income.

Table A.5: Model Fit - Annualized Income Overall

	Small-Firm		Large-Firm		Self-Employment		Not-Working	
	Data	*Simulation*	*Data*	*Simulation*	*Data*	*Simulation*	*Data*	*Simulation*
Mean	57.3	58.1	76.9	76.3	71.1	72.4	9.9	9.9
Standard deviation	33.0	31.7	49.8	47.2	80.3	75.0	3.6	3.6

Notes: Annualized income is measured in thousands of AUD. Simulation of income at t takes as given the empirical state at t and uses the last observed belief in the sample as the best estimate of individual sector ability. Not-working income statistics are conditional on receiving positive not-working income.

We also assess goodness of fit by taking as given the initial state observed in the data (at t_{i0}) and simulating forward the model. This exercise captures the transitions generated by the model. Figures A.1 and A.2 show that when we account for all the transitions generated by the model we continue to fit the data very well, remaining inside or very close to the confidence interval over the life cycle for both sector choices and income.

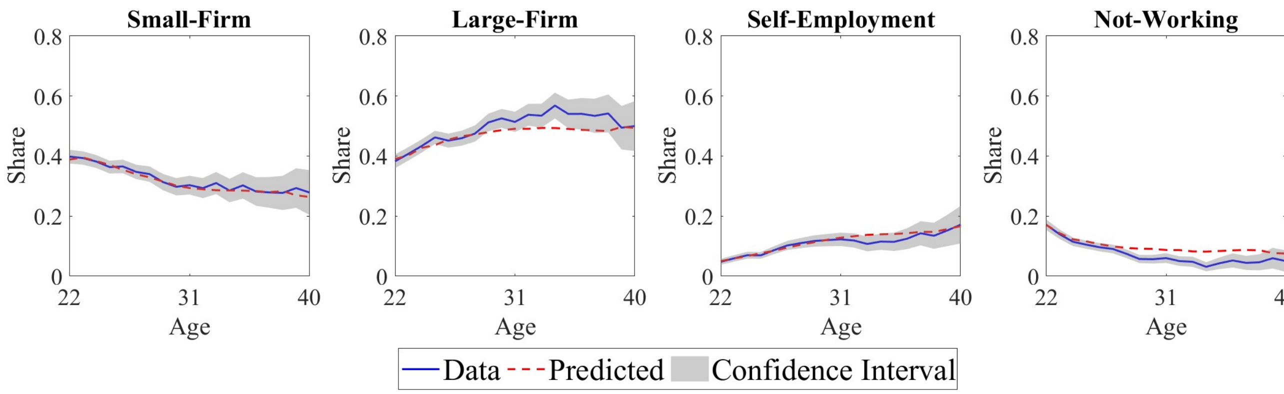


Figure A.1: Model Fit - Forward Simulated Sector Choices Over the Life Cycle

Notes: Shaded area corresponds to the 95% confidence interval around the data. Simulation of choices only takes as given the initial empirical state at t_{i0} and simulates forward from then.

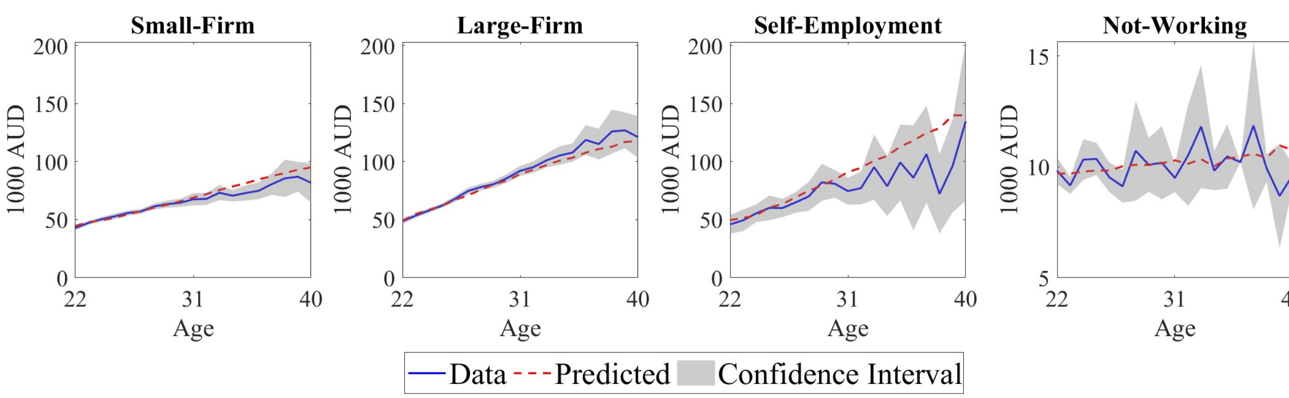


Figure A.2: Model Fit - Forward Simulated Annualized Income Over the Life Cycle

Notes: Shaded area corresponds to the 95% confidence interval around the data. Simulation of income only takes as given the initial empirical state at t_{i0} and simulates forward from then; it uses the last observed belief in the sample as the best estimate of individual sector ability. Not-working income statistics are conditional on receiving positive not-working income.

C Results Appendix

C.1 Parameter Estimates

Table A.6: Weekly Income

	Small-Firm		Large-Firm		Self-Employment	
	coeff	se	coeff	se	coeff	se
Constant	0.820	0.008	0.902	0.009	0.724	0.046
College or more	0.118	0.012	0.254	0.012	0.408	0.077
Initial wealth (IHS)	0.0063	0.0005	0.0044	0.0007	0.0183	0.0024
Small-firm experience						
$1\{exp_{PS} \geq 1\}$	0.089	0.006	-0.130	0.013		
$1\{exp_{PS} \geq 2\}$	0.052	0.006	0.157	0.023	0.216	0.035
$1\{exp_{PS} \geq 3\}$	0.068	0.007	-0.057	0.021		
$1\{exp_{PS} \geq 4\}$	0.080	0.007	0.174	0.022		
$1\{exp_{PS} \geq 5\}$					0.253	0.097
$1\{exp_{PS} \geq 6\}$	0.070	0.007	0.149	0.025	-0.408	0.116
$1\{exp_{PS} \geq 7\}$					0.234	0.112
$1\{exp_{PS} \geq 9\}$	0.144	0.014	0.160	0.069		
Large-firm experience						
$1\{exp_{PL} \geq 1\}$			0.159	0.007	0.263	0.034
$1\{exp_{PL} \geq 2\}$			0.134	0.005		
$1\{exp_{PL} \geq 3\}$	0.275	0.018	0.117	0.005		
$1\{exp_{PL} \geq 4\}$			0.133	0.008		
$1\{exp_{PL} \geq 5\}$	0.286	0.033	0.072	0.009	0.288	0.087
$1\{exp_{PL} \geq 6\}$	-0.136	0.034	0.083	0.007		
$1\{exp_{PL} \geq 7\}$	0.157	0.048	0.147	0.007		
$1\{exp_{PL} \geq 9\}$	0.484	0.062	0.326	0.018		
Self-employment experience						
$1\{exp_{SE} \geq 1\}$	0.209	0.029				
$1\{exp_{SE} \geq 2\}$	-0.131	0.029	0.298	0.125		
$1\{exp_{SE} \geq 3\}$			-0.061	0.136	0.199	0.028
$1\{exp_{SE} \geq 5\}$	0.402	0.096				
$1\{exp_{SE} \geq 6\}$					0.311	0.066
$1\{exp_{SE} \geq 9\}$					0.290	0.088
Obs	6,410		8,693		1,709	

Notes: This table includes point estimates (coeff) and standard errors (se) corrected for two-stage estimation using subsampling estimation over 100 subsamples without replacement. Weekly income is measured in 1000 AUD. Steps functions were chosen to avoid out of sample return estimates after 10 years of experience, especially in the self-employment sector. Steps were chosen as the statistically significant steps from a preliminary OLS regression that included all possible steps in the first 10 years of sector experience. Hence, it is assumed that individuals reach the top of the productivity ladder by the 10th year in the sector. IHS stands for inverse hyperbolic sine.

Table A.7: Weekly Not-Working Income

	Extensive Margin		Intensive Margin	
	coeff	se	coeff	se
Constant	0.002	0.033	0.250	0.003
College or more	-0.774	0.051	-0.017	0.003
Age - 21	-0.029	0.011	0.002	0.001
$(\text{Age - }21)^2/100$	-0.056	0.061	-0.002	0.005
σ_0^2			0.009	0.001

Notes: This table includes point estimates (coeff) and standard errors (se) corrected for two-stage estimation using subsampling estimation over 100 subsamples without replacement. Columns *Extensive Margin* show the results from a probit regression of receiving any not-working income conditional on not-working. Columns *Intensive Margin* show the results from a linear regression of not-working income conditional on not-working and receiving not-working income. Parameter σ_0^2 is the variance of the not-working income shocks.

Table A.8: Utility Parameters

	coeff	se						
CARA parameter, ρ	0.508	0.080						
Scale of marginal utility of income, α_y	6.186	0.580						
	Small-Firm		Large-Firm		Self-Employment		Not-Working	
	coeff	se	coeff	se	coeff	se	coeff	se
Constant	-1.256	0.130	-2.360	0.181	-3.388	0.166		
Age-21	-0.023	0.003	0.008	0.004	0.001	0.005		
Initial wealth (IHS)	0.019	0.001	0.021	0.001	0.013	0.003		
Father: high school or more	0.089	0.031	0.285	0.029	0.024	0.043		
Father: white collar occupation	0.278	0.028	0.313	0.029	0.722	0.040		
Small-Firm at $t-1$	1.763	0.043	0.079	0.046	0.491	0.079		
Large-Firm at $t-1$	-0.016	0.044	1.941	0.044	-0.393	0.079		
Self-Employment at $t-1$	0.135	0.077	-0.609	0.076	3.627	0.099		
Not-Working at $t-1$							2.030	0.035
Missing Father Information								
Education missing	-0.507	0.033	-0.628	0.030	-0.638	0.056		
Occupation missing	-0.231	0.035	-0.091	0.035	0.025	0.055		

Notes: This table includes point estimates (coeff) and standard errors (se) corrected for two-stage estimation using subsampling estimation over 100 subsamples without replacement. Indicators of missing father's information are included in order to maximize the number of observations available for estimation. IHS stands for inverse hyperbolic sine.

C.2 Solving the Model

In our empirical specification we leverage the observed variation in our sample as much as possible. Hence, we specified that individuals in the estimated model make sectoral choices from their entry into the labor market at age t_0 until age $\bar{t}=49$, and for every age $\bar{t}<t\leq T$ they must remain in the same sector they chose at age $\bar{t}$. The value of arriving at age $\bar{t}+1$ with state $z_{i\bar{t}+1}$ after choosing alternative j at $\bar{t}$, denoted $V_{ji\bar{t}+1}(z_{i\bar{t}+1})$, is given by:

$$V_{ji\bar{t}+1}(z_{i\bar{t}+1}) = E\left[\sum_{t=\bar{t}+1}^{T}\beta^{t-(\bar{t}+1)}u_{jit}(y_{jit},h_{it},d_{it-1})\middle| z_{i\bar{t}+1},\bar{d}_{ji}\right] \tag{A.22}$$

where $\bar{d}_{ji} = \{d_{ji\bar{t}+1}, \ldots, d_{jiT}\}$ is the sequence of alternative j indicators with $d = 1\ \forall d \in \bar{d}_{ji}$. Equation (A.22) captures the fact that choices are no longer made after age $\bar{t}$ but income uncertainty remains. We use the following algorithm containing a sieve approximation to obtain the value function at any age $t \leq \bar{t}$:[33]

- *Step 1*. If $t = \bar{t}$, compute the conditional value function as:

$$v_{ji\bar{t}}(z_{i\bar{t}}) = E\left[u_{ji\bar{t}}(y_{ji\bar{t}}, h_{i\bar{t}}, d_{i\bar{t}-1}) + \beta V_{ji\bar{t}+1}(z_{i\bar{t}+1})\,|\, z_{i\bar{t}}, d_{ji\bar{t}} = 1\right] \tag{A.23}$$

  where no approximation of the continuation value is needed as $V_{ji\bar{t}+1}(z_{i\bar{t}+1})$ is a known analytical function of the parameters given by (A.22).

- *Step 2*. Let $t = t-1$. Taking advantage of the Type I Extreme Value distribution of the preference shocks compute the continuation value as

$$V_{it+1}(z_{it+1}) = \ln\left(\sum_{j=0}^{3} \exp\left\{v_{jit}(z_{it+1})\right\}\right) \tag{A.24}$$

- *Step 3*. Obtain a parametric version of the continuation value $V_{it+1}(z_{it+1})$ by using linear regression of $V_{it+1}(z_{it+1})$ on a flexible polynomial of the state z_{it+1} with interactions. Let the coefficients of this regression be denoted Ω_{t+1}.

- *Step 4*. Obtain the conditional value function in equation (7) for each alternative j using the parameters Ω_{t+1} and the evolution of the state (induced by choice j at t) to approximate the continuation value.[34]

- *Step 5*. If $t = t_0$, stop. Otherwise, go back to Step 2.

At the end of this process we obtain a collection $\{\Omega_r\}_{r=t_0+1}^{\bar{t}}$ of parameters that approximate the continuation value for every age $t_0 \leq t \leq \bar{t}-1$.

[33] See for instance Arcidiacono et al. (2013).

[34] The expectation of the value function is obtained numerically using Gauss–Hermite quadrature. If $Y \sim \mathcal{N}\left(\mu, \sigma^2\right)$ then

$$\mathbb{E}[f(Y)] = \frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{\infty} f(y)e^{-\frac{(y-\mu)^2}{2\sigma^2}}dy \approx \frac{1}{\sqrt{\pi}}\sum_{i=1}^{S}\omega_i f\left(\sqrt{2}\sigma x_i + \mu\right)$$

where (x^s, ω^s) are Gauss-Hermite quadrature nodes and associated weights, and S is the number of nodes.

C.3 A Counterfactual Cut to Unemployment Benefits

In order to assess how unemployment benefits affect career choices we simulate choices under a counterfactual scenario in which the unemployment benefits in equation (2) are cut in half. Under this counterfactual, if individuals choose not to work ($j = 0$) their weekly income is given by:

$$y_{0t} = v_t \cdot \frac{1}{2} \left(f_0(h_t^0; \theta_0) + \sigma_0 \eta_{0t} \right) \tag{A.25}$$

Results in Table A.9 indicate that there are four main consequences of this policy. First, in response to the reduction of monetary incentives, the overall share of not-working individuals drops by 1.2 percentage points. Second, although the share of not-working individuals drops, the share of individuals who try self-employment remains at 40 percent and the overall rate of self-employment remains at 11.8 percent. Third, the decline in economic incentives for not-working slightly lowers the average self-employment ability of those who enter self-employment. Finally, the present value of income of those who try entrepreneurship increases by 0.8 percent. This small increase in PVI results from the overall increase in labor market participation, which offsets the negative effect in the average quality of self-employed individuals.

Table A.9: Self-Employment Life Cycle Behavior Under a Counterfactual Reduction of 50% in Unemployment Benefits

	Baseline	*50% Reduction*
Tried by age 40 (%)	40	40
Present value of income if tried by age 40	833	840
Overall rate of entrepreneurship (%)	11.8	11.8
Entry		
Transition rate from small firms (%)	4.6	4.6
Transition rate from large firms (%)	1.5	1.5
Transition rate from not-working (%)	2.7	2.8
Ability at 1st entry from small firms	103	99
Ability at 1st entry from large firms	140	138
Ability at 1st entry from not-working	-116	-127
Exit		
Overall exit rate from entrepreneurship (%)	16.1	16.0
Transition rate into small firms (%)	9.0	9.0
Transition rate into large firms (%)	4.7	4.7
Transition rate into not-working (%)	2.5	2.4
Not-Working		
Overall rate of not-working (%)	11.6	10.4

Notes: Column *Baseline* contains the information of the same column in Table 8. Column *50% Reduction* corresponds to a simulation under which the income when not working is cut to half.

References

Antonovics, Kate and Limor Golan, "Experimentation and Job Choice," *Journal of Labor Economics*, 2012, *30* (2), 333–366.

Arcidiacono, Peter, Patrick Bayer, Federico A. Bugni, and Jonathan James, "Approximating High-dimensional Dynamic Models: Sieve Value Function Iteration," in Eugene Choo and Matthew Shum, eds., *Structural Econometric Models (Advances in Econometrics Vol. 31)*, Bingley: Emerald Group Publishing Limited, 2013, pp. 45–95.

Åstebro, Thomas and Peter Thompson, "Entrepreneurs, Jacks of All Trades or Hobos?," *Research Policy*, 2011, *40* (5), 637–649.

Ayyagari, Meghana, Asli Demirguc-Kunt, and Vojislav Maksimovic, "Small vs. Young Firms across the World. Contribution to Employment, Job Creation, and Growth," Policy Research Working Paper WPS5631, The World Bank, Development Research Group, 2011.

Brown, Charles and James Medoff, "The Employer Size-wage Effect," *Journal of Political Economy*, 1989, *97* (5), 1027–1059.

DeGroot, Morris H., *Optimal Statistical Decisions*, McGraw Hill, 1970.

Dillon, Eleanor W. and Christopher T. Stanton, "Self-Employment Dynamics and the Returns to Entrepreneurship," NBER Working Paper 23168, 2017.

Ehrlich, Isaac, Dunli Li, and Zhiqiang Liu, "The Role of Entrepreneurial Human Capital as a Driver of Endogenous Economic Growth," *Journal of Human Capital*, 2017, *11* (3), 310–351.

Elfenbein, Daniel W., Barton H. Hamilton, and Todd R. Zenger, "The Small Firm Effect and the Entrepreneurial Spawning of Scientists and Engineers," *Management Science*, 2010, *56* (4), 659–681.

Evans, David S. and Boyan Jovanovic, "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints," *The Journal of Political Economy*, 1989, pp. 808–827.

Fox, Jeremy T., "Firm-size Wage Gaps, Job Responsibility, and Hierarchical Matching," *Journal of Labor Economics*, 2009, *27* (1), 83–126.

Friedline, Terri, Rainier D Masa, and Gina AN Chowa, "Transforming wealth: Using the inverse hyperbolic sine (IHS) and splines to predict youth's math achievement," *Social science research*, 2015, *49*, 264–287.

Glaeser, Edward L., Sari Pekkala Kerr, and William R. Kerr, "Entrepreneurship and Urban Growth: An Empirical Assessment with Historical Mines," *Review of Economics and Statistics*, 2015, *97* (2), 498–520.

Hamilton, Barton H., "Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-employment," *Journal of Political Economy*, 2000, *108* (3), 604–631.

Hessels, Jolanda, Cornelius A. Rietveld, A. Roy Thurik, and Peter van der Zwan, "The Higher Returns to Formal Education for Entrepreneurs versus Employees in Australia," *Journal of Business Venturing Insights*, 2020, *13*, e00148.

Hincapié, Andrés, "Entrepreneurship over the Life Cycle: Where Are the Young Entrepreneurs?," *International Economic Review*, 2020, *61* (2), 617–681.

Hout, Michael and Harvey Rosen, "Self-employment, Family Background, and Race," *Journal of Human Resources*, 2000, *35* (4), 670–692.

Hundley, Greg, "Family Background and the Propensity for Self-employment," *Industrial Relations*, 2006, *45* (3), 377–392.

Hurst, Erik and Benjamin W. Pugsley, "What Do Small Businesses Do?," NBER Working Paper 17041, 2011.

_ and _ , "Wealth, Tastes, and Entrepreneurial Choice," in John Haltiwanger, Eric Hurst, Javier Miranda, and Antoinette Schoar, eds., *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, University of Chicago Press, 2017, pp. 111–152.

James, Jonathan, "Ability Matching and Occupational Choice," SSRN Scholarly Paper ID 1937879, 2011.

Jovanovic, Boyan, "Job Matching and the Theory of Turnover," *Journal of Political Economy*, 1979, *87* (5), 972–990.

Klepper, Steven, "Spinoffs: A Review and Synthesis," *European Management Review*, 2009, *6* (3), 159–171.

Lazear, Edward P., "Entrepreneurship," *Journal of Labor Economics*, 2005, *23* (4), 649–680.

Miller, Robert A., "Job Matching and Occupational Choice," *Journal of Political Economy*, 1984, *92* (6), 1086–1120.

Molina-Domene, Maria, "Specialization Matters in the Firm Size-wage Gap," CEP Discussion Paper 1545, 2018.

Pavan, Ronni, "Career Choice and Wage Growth," *Journal of Labor Economics*, 2011, *29* (3), 549–587.

Pence, Karen M, "The role of wealth transformations: An application to estimating the effect of tax incentives on saving," *Contributions in Economic Analysis & Policy*, 2006, *5* (1).

Schumpeter, Joseph A., *The Theory of Economic Development; an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*, Cambridge, MA: Harvard University Press, 1934.

Sørensen, Jesper B., "Bureaucracy and Entrepreneurship: Workplace Effects on Entrepreneurial Entry," *Administrative Science Quarterly*, 2007, *52* (3), 387–412.

Stuart, Toby E. and Waverly W. Ding, "When Do Scientists Become Entrepreneurs? The Social Structural Antecedents of Commercial Activity in the Academic Life Sciences," *American Journal of Sociology*, 2006, *112* (1), 97–144.

Todd, Petra E. and Weilong Zhang, "A Dynamic Model of Personality, Schooling, and Occupational Choice," *Quantitative Economics*, 2020, *11* (1), 231–275.

Wagner, Joachim, "Are Young and Small Firms Hothouses for Nascent Entrepreneurs? Evidence from German Micro Data," IZA Discussion Paper 989, 2004.

Wallskog, Melanie, "Entrepreneurial Spillovers Across Coworkers," Working Paper, Duke University 2023.

Wilkins, Roger and Inga Laß, "The Household, Income and Labour Dynamics in Australia Survey: Selected Findings from Waves 1 to 16," Technical Report, Melbourne Institute: Applied Economic & Social Research, 2018.