The Macroeconomic Implications of Uncertainty and Learning for Entrepreneurship*

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Abstract

Entrepreneurs face non-trivial uncertainty upon entry and they gradually learn about their innate ability to reduce uncertainty over the life cycle. In this paper, we first establish empirical facts on entrepreneurial productivity uncertainty and learning using novel subjective belief data, which is consistent with life-cycle income profiles and outcomes of self-employed from the U.S. administrative data. We then introduce uncertainty faced by entrepreneurs and an endogenous learning process that are well-disciplined by the data into a heterogeneous agent life cycle model with occupational choice and financial frictions. Finally, we use the model to quantitatively exploit two important macroeconomic implications: (1) the sources of secularly declining entrepreneurship in the U.S. in the recent three decades; and (2) how large-scale policies aimed at reviving entrepreneurship should be designed, e.g. progressive personal income tax v.s flat tax. We show that our model with life-cycle learning dynamics changes the view to think about those macro aspects regarding entrepreneurship compared to the existing literature.

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1 Introduction

An increasing number of research has documented that measures of entrepreneurship in the U.S. have declined in recent decades (Decker et al., 2014a,b; Salgado, 2020), which has generated considerable concern among scholars and policy makers.[1] Under the current U.S. tax system, passthrough business owners are subject to a progressive personal income tax schedule. As taxes can potentially change people's incentive to be an entrepreneur (Gentry and Hubbard, 2000; Wen and Gordon, 2014), it is thus important to understand how the current U.S. progressive personal income tax scheme affects the entry of entrepreneurs and the overall entrepreneurship, and how entrepreneurs should be taxed in terms of tax progressivity in order to promote entrepreneurship.

In this paper, we answer these questions by highlighting the entry margin of entrepreneurs with respect to taxes from the perspective of life cycle. The young potential entrants, operating their future businesses at relatively small scale due to low wealth level and facing higher uncertainty, may prefer more progressive tax since it imposes lower tax burden and provides higher insurance value. The old successful incumbent entrepreneurs, on the other hand, may want less progressive taxes. An extreme case is a proportional tax with zero progressivity.

We show that the current U.S. progressive personal income tax system is superior to a counterfactual flat tax reform in terms of promoting entrepreneurship in a heterogeneous agent life cycle model with occupational choice and financial frictions. Our key innovation is to introduce non-trivial uncertainty faced by entrepreneurs and an endogenous learning process about their innate entrepreneurial ability such that the uncertainty can be reduced via learning over the life cycle. Both elements are supported and disciplined by novel subjective belief survey data on business owners. The intuition behind is that if young agents do not enter to learn about their innate entrepreneurial ability, they will not choose to be an entrepreneur when they are old either since the value of learning is decreasing in age and it is not worthwhile to take the risk when agents are close to the end of their life cycle. Progressive taxation favors the young, thus encouraging them to experiment with entrepreneurship earlier. The main takeaway is that without encouraging agents to enter to discover their entrepreneurial aptitudes, those with high innate productivity may never become an entrepreneur, and thus entrepreneurship-boosting policies should prioritize the young as it will eventually benefit the old successful entrepreneurs who grow up from the young talents.

We start by establishing empirical facts on entrepreneurial productivity uncertainty and learning using subjective belief data from the Panel Studies of Entrepreneurial Dynamics

[1] The secular decline in entrepreneurship is an important indicator of declining business dynamism, often associated with less creative destruction, which may have important macroeconomic repercussions.

(PSED) to motivate our model. First, we find that entrepreneurs face large uncertainty upon entry in the sense that entrant entrepreneurs forecast their business performances in terms of sales with non-trivial errors. Furthermore, incumbent entrepreneurs update their expectation on their business performances using new observed information. More specifically, for every dollar of realized sales that is above their forecasts made in the previous period, entrepreneurs raise forecasts on future sales by 67 cents. The productivity learning process is also consistent with the pattern that exit rate of entrepreneurs is decreasing in the duration of their businesses from the Panel Studies of Income Dynamics (PSID).

We then develop a dynamic general equilibrium heterogeneous agent life cycle model. At the beginning of each period, individuals choose between being a worker and an entrepreneur based on heterogeneous characteristics including occupation-specific abilities, beliefs, assets, and age. Workers earn wage income, while entrepreneurs earn business income in terms of profits by running their own businesses subject to collateral constraints. Both wage and business income are subject to the same nonlinear income tax schedule *à* la Heathcote, Storesletten, and Violante (2017). We also introduce non-pecuniary utilities, which is manifested as a permanent difference in the taste of being an entrepreneur across agents. In addition, we allow for voluntary retirement and bequests to capture the incentive to work and accumulate assets at older ages.

The key elements of our framework are entrepreneurial productivity learning and a finite life cycle. In the model, agents are born with a permanent innate entrepreneurial productivity. An agent does not observe this innate productivity but only has a belief about it upon entering the labor market. Agents make occupation choice with their beliefs about the innate entrepreneurial ability before the realization of idiosyncratic shocks. The entrepreneurial productivity shock is a combination of their innate productivity with a transitory shock, with which they gradually update their belief about their innate productivity. Individuals can only observe the realized productivity shock that contains information on their innate ability through actively engaging in entrepreneurial production. As agents age, they hold more assets and predict their future productivity with higher precision.

Our setup deviates from a class of quantitative heterogeneous agent occupation choice model widely used in the macroeconomic literature on entrepreneurship incluldng Quadrini (2000) and Cagetti and De Nardi (2006) in three dimensions. First, the occupation choice in our model is made before the realization of idiosyncratic shocks, which necessitates insurance provided by the progressive taxation. Otherwise, agents can always self-select the occupation with higher incomes shock realization. From this perspective, our set-up is in the same spirit as in Hopenhayn and Vereshchagina (2009). Second, the entrepreneurial productivity process in our model is endogenous since agents' beliefs about the innate productivity are shaped by the occupation choice made in previous periods. Therefore, policy instruments are able to affect the entrepreneurial productivity process through influencing agents' entrepreneurial choice, while in the existing literature, productivity processes are exogenously given and thus invariant to policy intervention.[2] Third, the interaction between learning and a finite life span brings about novel implications that does not exist in existing models. The earlier the uncertainty solved, the longer periods an entrepreneur shall expect to operate, thus receiving more earnings conditional on they find themselves innately productive. Therefore, the value of learning is decreasing in age. Due to these key deviations from the existing frameworks, our model deliver different policy implications. In existing models with infinite horizon and purely exogenous entrepreneurial productivity process, the age of becoming an entrepreneur does not matter. Hence, the policy considerations put more emphasis on the incumbent high income entrepreneurs. Our model incorporating lifecycle learning dynamics highlights the entry margin and the timing of being an entrepreneur since without young talented agents becoming entrepreneurs first, those old large successful firms may never show up.

We calibrate model parameters using the method of simulated moments (MSM) to accommodate information from several nationally representative survey data. We use moments on the business forecasting process from PSED to discipline the entrepreneurial productivity learning and further exploit the survey questions on personality traits (e.g., love of business) for estimating parameters that govern non-pecuniary utilities of being an entrepreneur. We utilize the panel feature of the PSID to construct the hump-shaped age profile of entrepreneurial entry as well as declining exit rate of entrepreneurs in working age. While not directly targeted by the parameterization, our model is successful in matching salient features from both micro and macro data, such as income and wealth distribution as well as the entry and exit dynamics of entrepreneurs over the life cycle.

Armed with a well fitted and validated model, we proceed to deliver the main results—the current U.S. progressive tax scheme is superior to a counterfactual revenue-neutral flat tax reform in terms of promoting entrepreneurship. We fix the wage income tax schedule and vary the level of flat tax rate imposed to business income and find that the revenue-maximizing flat rate of around 20% achieves roughly the same tax revenue as the current U.S. progressive tax scheme. We further find that switching to a revenue-neutral flat business income tax schedule from the current progressive taxation reduces the overall entrepreneur share in the working-age population from 9% to 6%. It is not surprising that switching to a flax tax discourages entrepreneurship at younger ages since it imposes a higher tax burden and provides the young with lower insurance value, but more importantly, it further reduces

[2]The only exception is Bhandari and McGrattan (2021) that allows entrepreneurs to accumulate intangible assets as unmeasured productivity for production.

entrepreneurship at older ages due to the dynamic persistent effect of learning.

Moreover, we study the distributional effects across innate entrepreneurial ability types. We find that high type entrepreneurs lose more from the flat tax reform in terms of lifetime earnings. This is, again, in contrast to the standard results that high productivity entrepreneurs should benefit more from a flat tax scheme compared to a progressive one, with revenue controlled. The reason is that the counterfactual flat tax reform discourages young agents from experimenting with entrepreneurship to learn about their innate ability, and this mainly hurt those with high productivity since low type agents would never become an entrepreneur regardless of the information friction. Consequently, the occupation allocation is worsened and high type entrepreneurs' lifetime income becomes smaller.

To further shed light on the role of the uncertainty resolution through productivity learning, we consider a special case where agents perfectly know about their innate ability upon entering the labor market and entrepreneurs produce only subject to transitory productivity shocks. We refer to this case as perfect information hereafter. This is essentially the framework employed in the existing macro literature that studies risky entrepreneurial activities such as Hopenhayn and Vereshchagina (2009) and Boar and Knowles (2020), that can be nested by our benchmark model.

The case of perfect information serves several purposes. First, it provides counterfactual outcomes on how agents would have behaved if there were no uncertainty about innate ability, through which we are able to quantify the cost of such an uncertainty. Compared to the benchmark model with uncertainty about true types, switching to the perfect information scenario makes the high type agents gain more relative to the middle or low type agents. The logic is that without perfectly knowing the true types, even high type agents would spend some time being a worker since resolving the uncertainty takes time. Second, the case of perfect information helps isolate the strength of the learning channel from the asset accumulation one as it keeps only the latter. Our numerical exercise shows that under the benchmark with our calibrated parameters, the learning channel dominates the asset accumulation motive. More importantly, by conducting the same flat business tax exercise, we do not observe a persistent decline in entrepreneurship over the life cycle with perfect information. This shows the quantitative importance of incorporating uncertainty and learning into the framework to evaluate tax policy impacts.

Related Literature This paper contributes to several literatures. The first strand relates to modelling the determinants of entrepreneurship, with different aspects highlighted: wealth accumulation and financial friction (Cagetti and De Nardi, 2006; Quadrini, 2000), non-pecuniary benefits (Hamilton, 2000; Hurst and Pugsley, 2017), sweat equity and working hours contributed by business owners (Bhandari and McGrattan, 2021), risky nature of entrepreneurial activities (Boar and Knowles, 2020; Hopenhayn and Vereshchagina, 2009), and entrepreneurial productivity learning (Dillon and Stanton, 2018; Hincapié, 2020; Kerr, Nanda, and Rhodes-Kropf, 2014; Manso, 2016). Our work builds upon those papers, orchestrating a unified quantitative macro model with rich life cycle features such as wealth accumulation by earning income from own's labor inputs and bequests, learning, and non-pecuniary benefits. Compared to macro models such as Cagetti and De Nardi (2006); Quadrini (2000), our framework incorporates richer elements, e.g. learning, non-pecuniary benefits, motivated by subject belief and personal traits data on business owners. Compared to structural micro models such as Dillon and Stanton (2018); Hincapié (2020), the general equilibrium Aiyagari-styled setup enable us to use it to evaluate comprehensive large-scale government policy reforms. The reduced uncertainty via learning over the life cycle can also be seen as accumulation of a specific form of human capital, similar in spirit to Smith et al. (2019), Bhandari and McGrattan (2021), and Boerma and Karabarbounis (2022).

Second, our paper contributes to the existing literature on the taxation of entrepreneurs that has been focusing on different aspects including top marginal rates (Brüggemann, 2021; Imrohoroğlu, Kumru, and Nakornthab, 2018), the role of owner time in evaluating business income tax reform impacts (Bhandari and McGrattan, 2021), wealth and capital income tax (Boar and Knowles, 2020; Boar and Midrigan, 2022; Kitao, 2008), and redistribution and general equilibrium effects of personal income tax reform for both workers and business owners (Boháček and Zubrickỳ, 2012; Meh, 2005). In a relatively standard model with infinite horizon and exogenous entrepreneurial productivity process *à* la Cagetti and De Nardi (2006); Evans and Jovanovic (1989); Quadrini (2000), flat tax may favor high income high productivity entrepreneurs compared to a progressive scheme, controlling for tax revenue. This is mainly driven by the benefits gained by large profitable incumbent firms outweigh the loss suffered from potential entrants and low income entrepreneurs. Our setup deviates from those models by incorporating a realistic life cycle and entrepreneurial productivity learning with expost transitory shock. Without being an entrepreneur first to learn about innate ability, those highly successful firms may never emerge. This key dynamic effect reverses the tradeoff between gains from large successful entrepreneurs and loss from potential entrants and low income entrepreneurs via the flat tax reform. Models in Boar and Knowles (2020); Hopenhayn and Vereshchagina (2009) also feature expost risk but in which agents perfect know their entrepreneurial productivity upon entering the labor market, which can be perceived as a special case of our model. However, we show that embedding the uncertainty on innate ability about which agents gradually learn quantitatively matters for the impacts of tax policy analysis. Abstracting from such an uncertainty and learning process understates the effects of the flat tax reform in the sense that there is little dynamic persistent effect over the life cycle.

The third related literature concerns the macroeconomic implications of information uncertainty and learning, with different focuses: Boerma and Karabarbounis (2022) on persistent racial wealth gaps, Kozlowski, Veldkamp, and Venkateswaran (2020a,b) on the long-term belief-scaring effects of crisis such as the Great Recession and the Covid-19, Baley, Veldkamp, and Waugh (2020) on international trade, Bui et al. (2022) on their effects on international fluctuations and interaction with global value chains, Buera, Monge-Naranjo, and Primiceri (2011) on the evolution of market-oriented policies, Wee (2013) on persistent wage scars, and so on. We contribute to this literature by exploiting the role of uncertainty and learning in shaping the entrepreneurship as well as how they change our view to think about entrepreneurship-promoting policies.

Finally, our work attempts to estimate entrepreneurial productivity process combing both the subjective belief data on business owners with a quantitative macro model featuring rich micro heterogeneity. Better access to subjective belief data has enabled researchers to identify the decision-making process with uncertainty in many contexts such as educational choice (Delavande and Zafar, 2019), occupational choice (Arcidiacono et al., 2020), and job seeking process (Mueller, Spinnewijn, and Topa, 2021). Building upon Altig et al. (2020) which infers business risks using forecasting data at firm-level, we exploit the novel aspects of forecasting variables in the subjective belief survey data on business owners to directly estimate the entrepreneurial productivity process. The advantage of our approach is that we are not simply assuming a particular statistical distribution of income risks, e.g. log normal, as in earlier theoretical works. In fact, Wen and Gordon (2014) and Fossen (2009) come to completely opposite conclusions about the impact of tax prorgressivity on entrepreneurship in a similar static model with entrepreneurial choice simply due to the different assumptions on the functional forms of income shocks. Rather, with the aid of a quantitative life cycle framework that granularly models the incentives to be an entrepreneur, particularly asset accumulation with financial frictions, entrepreneurial productivity learning, and the interaction between them, the entrepreneurial productivity process in our model is purely endogenous that are shaped by rich lifecycle motives and choices.

2 Empirical facts on entrepreneurial productivity learning

We first rely on PSED to show that (1) entrant entrepreneurs do face large uncertainty upon entry; and (2) entrepreneurs update their forecasts on future business performances using new observed information to reduce the uncertainty, but the uncertainty is still non-trivial after learning. We use these empirical findings to both motivate and discipline the uncertainty faced by entrepreneurs and an endogenous learning process about their innate entrepreneurial ability. We then use PSID documenting the life cycle dynamics of entrepreneurship that is consistent with data patterns from PSED.

We define entrepreneurs in PSID as self-employed household heads who are business owners, following Quadrini (2000).[3] We define entrepreneurs in PSED as nascent entrepreneurs (NE) who are active in business creation and actually produce.[4] In terms of legal forms, most of the entrepreneurs considered in both PSID and PSED are passthrough business owners, who are subject to personal income taxation.[5]

Variable definitions We use PSED I that covers 1998 to 2004 and surveys a sample of NEs for four waves. We rely on survey questions on NEs' expectation regarding their businesses' future performances to construct variables on learning. In wave 1 (year 0), the survey asks expected sales in both the first full year of operation and in the fifth full year of operation. Respondents in wave 2-4 (year 1-3) are asked to report sales in current year and predict sales in the fifth full year of operation again.[6]

Based on the data we have, we denote forecasts on sales made in period 0 for periods 1-5 by $\texttt{ESale}_0^q$ for $q = 1, ..., 5$. Since the survey only provides $\texttt{ESale}_0^1$ and $\texttt{ESale}_0^5$, we linearly interpolate forecasts between them to generate $\texttt{ESale}_0^2$, $\texttt{ESale}_0^3$, and $\texttt{ESale}_0^4$. We denote realized sales in period 1,2,3 by $\texttt{RSale}_s$ for $s = 1, 2, 3$. We denote forecasts on sales made in period 1,2,3 for period 5 by $\texttt{ESale}_s^5$ for $s = 1, 2, 3$. Our main measure of forecast errors is the deviation of the realized sales in period s from an entrepreneur's period 0 forecast on its

[3] See Appendix A for a detailed discussion of alternative definitions of entreprenuers.

[4] See Appendix A for more detailed criteria on people who are considered as "nascent entrepreneurs" in PSED

[5] In PSED, more than 84% nascent entrepreneurs are passthroughs, and in PSID, around 67% of entrepreneurs are unincorporated which means the share of passthroughs should be higher than this number. See Appendix A for more details on the comparison between PSID, PSED, and other important data such as SCF and IRS.

[6] Following Altig et al. (2020), we focus on sales to capture firms' performance. The key reason we believe sales is a better variable for measuring business performances of entrepreneurs than employment is that in PSED, around half of the NEs choose to be "merely" self-employed, which means they would not have any employees.

sales for period s scaled by the sum of these two variables.[7] More specifically, forecast errors $\texttt{FError}_0^s$ in period $s = 1, 2, 3$ are constructed as

$$\texttt{FError}_0^s = \frac{\texttt{RSale}_s - \texttt{ESale}_0^s}{\texttt{RSale}_s + \texttt{ESale}_0^s} \tag{1}$$

Our main measure of forecast revision is the deviation of the prediction on sales for period 5 made in period s from the prediction on sales for period 5 made in period 0 scaled by the sum of the two variables. More specifically, forecast revision in period s on period-5 performance $\texttt{FRev}_s^5$ for $s = 1, 2, 3$ is constructed as

$$\texttt{FRev}_s^5 = \frac{\texttt{ESale}_s^5 - \texttt{ESale}_0^5}{\texttt{ESale}_s^5 + \texttt{ESale}_0^5} \tag{2}$$

Empirical findings We plot our main results in Figure 1 about the size and dynamics of entrepreneurial risks that will be informative about entrepreneurial productivity learning process.

(a) Distribution of forecast errors (b) Forecast errors & forecast revision

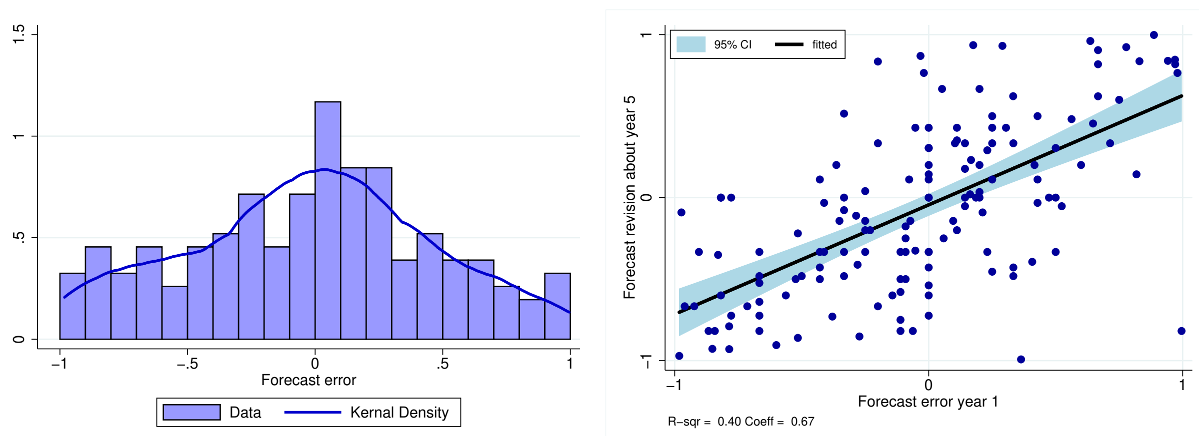

Figure 1: Size and evolution of entrepreneurial risks

Figure 1(a) presents the distribution of the forecast errors (smoothed using Kernel density estimation method) for year 1. As we can see from Figure 1(a), the distribution of $\texttt{FError}$ is nearly symmetric at year 1, with standard deviation around 0.40. Figure 1(b) shows how forecasts on sales in year 5 are revised after people observe their realized sales in year 1. More specifically, we regress forecast revision about period-5-sales made in period 1 on forecast errors in period 1. We obtain a R-square equal to 0.40, which suggests a strong linear relationship between forecast revision and forecast errors. The coefficient of 0.67 can

[7] We do normalization this way is to ensure the forecast errors fall within a certain bounded interval, in our case, $[-1, 1]$. Alternatively, we can define forecast error as $log(\texttt{RSale}_s) - log(\texttt{ESale}_0^s)$.

be interpreted as that for every dollar of realized sales that is above their forecasts made in the previous period, entrepreneurs raise forecasts on future sales by 67 cents. Through the vertical axis of Figure 1(b), we can see that the distribution of forecast revisions is very dispersed, suggesting information uncertainty is still large even after learning.

Exit Rate by Business Duration In Figure 2, the horizontal axis plots the number of years that an entrepreneur in PSID has running the business and the vertical axis represents the corresponding exit rate. Around 35% of entrepreneurs exit after one year. The exit rate decreases in the duration of businesses, and flattens out after around 8 years. This is consistent with the hypothesis that individuals are experimenting with entrepreneurship and only those who find themselves highly productive will stay (Dillon and Stanton, 2018; Hincapié, 2020; Kerr, Nanda, and Rhodes-Kropf, 2014; Manso, 2016): the selection through learning process explains the declining pattern of exit rate.

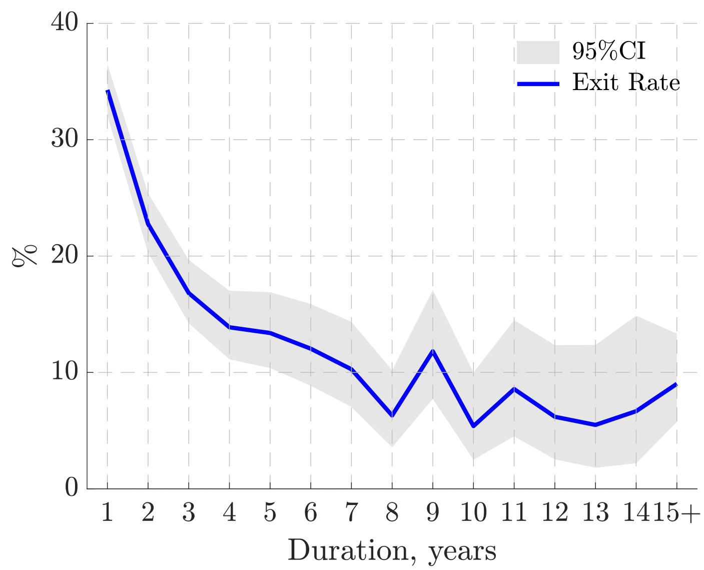

Figure 2: Exit rate by duration of current entrepreneurial spell

Entrepreneurship over the life cycle As shown in Figure 3, the entry and exit of entrepreneurs feature strong life cycle patterns. The entry rate increases with respect to age first, peaks at around age 45-50 at 3.2%, and then declines thereafter. The exit rate declines in working age, troughs at age 45-50, and then slightly increases, especially after the age 60 due to retirement.[8] That young entrepreneurs exit at a higher probability shown in Figure 3

[8]The entry rate is calculated as the proportion of household heads that are neither business owners nor self-employed in period t but become entrepreneurial households in period $t+1$. Similarly, the exit rate is calculated as the proportion of households heads that are entrepreneurs in period t but are not entrepreneurs in period $t+1$.

is consistent with Figure 2 since younger people are more likely to be first-time entrepreneurs or entrepreneurs with a shorter duration. This is also aligned with a more general pattern documented by Papageorgiou (2014) that occupational switching rate is declining in working age.

The overall share of entrepreneurs in the households is hump-shaped, peaking at middle-age, which is driven by both entry and exit dynamics. This is broadly consistent with empirical findings in Azoulay et al. (2020) that successful entrepreneurs are middle-aged using IRS K-1 and US Census Bureau business data which identifies the initial owners of pass-through firms.

(a) Entry rate (b) Exit rate (c) Share in Households

Figure 3: Entrepreneurship over the Life Cycle

3 Model

In this section, we build up a tractable quantitative macro framework with rich heterogeneity that affect entrepreneurial choice decisions. We focus on a steady state equilibrium and thus abstract from time subscripts.

3.1 Demographics and environment

Time is discrete and the economy is populated by J overlapping generations. In each period, a continuum of new individuals are born. The mass of cohorts grows at rate g_n. Each individual may die with a positive age-dependent probability, with the conditional survival probability from age j to age $j+1$ denoted as ψ_j. The survival probability in the final period of life cycle is $\psi_J = 0$. There are no annuity markets and individuals derive warm glow utility through leaving assets towards future generations. Therefore, the economy features both accidental and voluntary bequests.

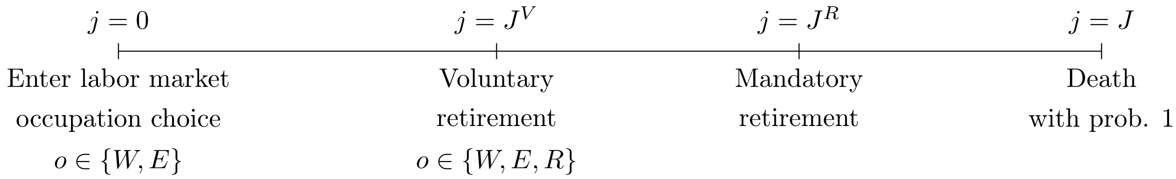

Figure 4: Life cycle of the model

Age is indexed by $j \in \{1, ..., J\}$. We assume individuals of age less than 21 as inactive. Model period 1 refers to age 21, when an individual just enters the labor market. The youngest age to claim retirement and receive social security benefits is J^V and the mandatory retirement age is J^R—after which all individuals have to retire regardless of their current employment status. Hereafter we refer to periods before J^V as normal working ages, and periods between J^V and J^R as voluntary retirement ages. For simplicity, our model abstract from health shocks and medical expenditure shocks at older ages.

We assume that all individuals enter the economy with zero initial assets, i.e. $a_0 = 0$. Individuals receive a certain amount of bequest with some probability over the life cycle in an unanticipated way.[9] The time endowment for each individual is one for each period. Before agents get retired, they make occupation choices $o \in \{W, E\}$ at each period: to work as employees (W), or to own and operate a private business (E). The non-employed are interpreted as workers working zeros hours in our model.

When first entering the labor market, an individual draws from a normal distribution $\mu \sim N(\nu_e, \nu_e^2)$ her individual-specific innate entrepreneurial productivity, which is unobservable to the individual. Instead, individual form a belief about the distribution of her innate ability and can only gradually learn about it through conducting entrepreneurial activities.

More specifically, the occupation choice is made based on idiosyncratic characteristics that is summarized by states $\mathbf{x}_j = (x_e,\ a_j,\ \epsilon_{w,j},\ \tilde{\mu}_{e,j},\ \tilde{\nu}_{e,j},\ \epsilon_{e,j})$ for an individual with age j, where x_e is a individual-fixed Love of Business (LoB) characteristic, a is assets, ϵ_w is the wage income shock in paid-employment, $\tilde{\mu}_e$ and $\tilde{\nu}_e$ are two parameters that govern entrepreneurial learning process following Bayesian fashion, ϵ_e is the realized entrepreneurial productivity shock, i.e., the signal about the individual's true entrepreneurial productivity observed by the individual.

Before describing individuals' problem in detail, we outline the precise timing of the model within a period, as summarized in Figure 5. Note that the occupation in period j is made at the end of period $j-1$. Conditional on being an entrepreneur, an individual observe a signal

[9] This means individuals receive bequests as a lump sum transfer in terms of assets, which does not enter the value function.

about her innate entrepreneurial productivity ϵ_e, with which she chooses capital and labor for production and updates her belief about her innate entrepreneurial productivity. After receiving incomes subject to taxes, she next makes decisions on consumption and saving. Finally, the entrepreneur decides her occupation for next period. Conditional on being a worker, the individual receives wage income and makes consumption/saving decision as well as the occupational choice decision.

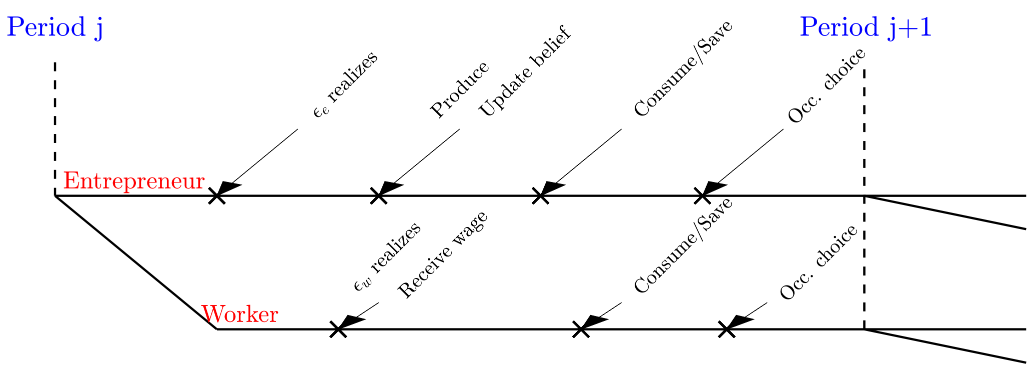

Figure 5: Timeline within one model period in normal working ages

3.2 Preferences

Individuals maximize the expected utility function over sequences of consumption and leisure $\{c_j, l_j\}_{j=1}^{J}$:

$$\mathbb{E}\{\sum_{j=1}^{J} \beta^{j-1} (\prod_{a=0}^{j-1} (1-\psi_a))[(1-\psi_j) u\,(c_j, l_j) + \psi_j \mathcal{V}(a_j)]\} \tag{3}$$

where β is the discount factor. The expectation is taken with respect to the stochastic processes governing idiosyncratic labor productivity and learning about the innate entrepreneurial productivity. Both workers and entrepreneurs are endowed with one unit of productive time. An individual's leisure l_j is determined by:

$$l_j = 1 - (\phi_{w,0} + h_j)\mathbb{I}_{\{h_j>0\}} - g(x_e)\mathbb{I}_{\{o_j=E\}}$$

For workers of age $j < J^R$, they split the time endowment between work h_j and leisure l_j. If an individual chooses non-employment ($h = 0$), her leisure l is just equal to one. If the individual works for positive hours, i.e. $h > 0$, besides the disutility from working hours, she suffers an extra fixed utility cost $\phi_{w,0}$. For entrepreneurs ($o = E$), they pay a fixed utility cost $g(x_e)$, denominated in productive time units. The fixed cost is a function of the LoB state x_e, which captures the fact that people with a high x_e may be subject to a lower level of disutility of being an entrepreneur. Hurst and Pugsley (2011, 2017) document that non-pecuniary utilities play a first-order role in the business formation decision. Hamilton, Papageorge, and Pande (2019) and Jones and Pratap (2020) find that non-pecuniary utilities help to rationalize the existence of low productivity and low income entrepreneurs.

3.3 Asset market and borrowing constraints

Individuals have access to competitive financial intermediaries, who receive deposits from both workers and entrepreneurs, and rent out capital to entrepreneurs. We focus on within-period borrowing, or capital rental for production purposes. We do not allow borrowing for inter-temporal consumption smoothing, which translates into non-negative financial wealth, i.e. $a \geq 0$. The zero-profit condition of the intermediaries implies a capital rental rate of $r + \delta$ where r is the deposit rate and δ is the depreciate rate of capital.

3.4 Government

The government in our model (meant to stand in for all levels−federal, state, and local— in the real world) consumes resources, collects tax revenues, and operates a social security system. The government finances a exogenously-given expenditure G with consumption and personal income taxes. Consumption income taxes is proportional at rate τ_c. Personal income tax schedule $T(y)$ is common to worker and entrepreneurs and is progressive in pre-government income y. y corresponds to wage income for workers or business incomes (profits) for entrepreneurs.

The government also operates a balanced pay-as-you-go social security system. Individuals receive social security benefits z that are independent of their contributions and are financed by social security tax τ_{ss}, which is linear in total income (the sum of wage and business income). τ_{ss} is exogenously given.

3.5 Entrepreneurial productivity learning process

Upon entering the labor market, each individual draws a permanent entrepreneurial productivity from a normal distribution $\mu \sim \mathcal{N}(\mu_e, \nu_e^2)$, which is the individual's innate entrepreneurial productivity. Individuals do not know their innate entrepreneurial productivities. They get the chance to learn it every time they choose to become an entrepreneur. The occupation choice is made based on individuals' beliefs about their innate entrepreneurial productivity where the beliefs are updated in a Bayesian fashion.

In other words, each individual's belief about their true entrepreneurial productivity is just equal to the true population distribution of entrepreneurial productivity $\mathcal{N}(\mu_e, \nu_e^2)$ before they enter the labor market. After choosing to become an entrepreneur, individuals receive an $\epsilon_{e,n}$ shock, which acts as a signal of their innate entrepreneurial productivity. Note that n captures the number of periods for which an individual works as an entrepreneur. The signal consists of two parts: the true entrepreneurial productivity and an innovation that is independently and identically distributed across individual states. That is,

$$\epsilon_{e,n} = \mu + \varepsilon_n$$

where ε_n follows i.i.d. $\sim \mathcal{N}(0, \sigma_e^2)$.

Since both the innate entrepreneurial productivity and the innovation are normally distributed, the signal $\epsilon_{e,n}$ is also normally distributed. Moreover, since both the prior and the signal are normally distributed, the posterior distribution after any number of observed signals will also be normally distributed. The distribution of the posterior beliefs after observing nth signals can be completely described by its mean $\mu_{e,n}$ and variance $\nu_{e,n}^2$. Using Bayes' theorem and the assumptions of normal densities, one can write how the belief evolves as follows:

$$\tilde{\nu}_{e,n}^2 = \begin{cases} \frac{\nu_e^2 \sigma_e^2}{n\nu_e^2 + \sigma_e^2} & \text{if} \quad o = E \\ \tilde{\nu}_{e,n-1} & \text{otherwise} \end{cases} \tag{4}$$

$$\tilde{\mu}_{e,n} = \begin{cases} \tilde{\nu}_{e,n}^2 \left(\frac{\tilde{\mu}_{e,n-1}}{\tilde{\nu}_{e,n-1}^2} + \frac{\epsilon_{e,n}}{\sigma_e^2} \right) & \text{if} \quad o = E \\ \tilde{\mu}_{e,n-1} & \text{otherwise} \end{cases} \tag{5}$$

n captures the number of periods for which an individual have worked as an entrepreneur, which is a sufficient statistic for computing the variance $\nu_{e,n}^2$. Conditioned on other factors, individuals obtain higher precision about innate abilities as they run businesses for more periods. As shown in equation (4), given m, the posterior variance $\tilde{\nu}_{e,n}^2$ is increasing in both the variance of innate productivity dispersion ν_e^2 and variance of i.i.d. shocks σ_e^2. That is, the *absolute sizes* of innate productivity and i.i.d. shocks jointly determine the precision of belief given n. Equation (5) further shows that the posterior mean $\tilde{\mu}_{e,n}$ is a weighted average of prior mean $\tilde{\mu}_{e,n-1}$ and size of the i.i.d. shock $\epsilon_{e,n}$, weighted by the size of prior variance $\tilde{\nu}_{e,n-1}^2$ and i.i.d. shock variance σ_e^2. As σ_e^2 increases, individuals put a lower weight on the most recent i.i.d. shock $\epsilon_{e,n}$ relative to the prior, i.e., the *relative size* of i.i.d. shocks to innate productivity determines how fast individuals learn about their innate productivity.

3.6 Income processes

Wage income process Individuals with age j receive a wage income $y_{w,j}$ that is additive in the general equilibrium efficiency wage w, an exogenous age-dependent component θ_j, a permanent productivity χ_w, and a persistent idiosyncratic wage income shock $\epsilon_{w,j}$:

$$\log y_{w,j} = \log \omega + \log \theta_j + \log \chi_w + \log \epsilon_{w,j}$$

Entrepreneurial production and business income At the beginning of each period, after observing the signal to the innate entrepreneurial productivity ϵ_e, given market prices, entrepreneurs make decisions on how much capital k to rent and how much labor n_b to hire for production. They gains access to a decreasing-return-to-scale technology:

$$e^{\epsilon_e} f(k, n) = e^{\epsilon_e} (k^{\alpha} n_b^{1-\alpha})^{\eta} \tag{6}$$

where $\eta < 1$ is the span-of-control parameter. A share η of output goes to factor of inputs. Out of this, a fraction of α is going to capital and $1 - \alpha$ going to labor.

Normalizing entrepreneurial output price to be 1, business income is calculated as revenue net labor and capital rental costs:

$$\begin{aligned} \pi(a, \epsilon_e) = & \max_{k, n_b} \{ e^{\epsilon_e} f(k, n_b) - \omega n_b - (r + \delta) k \} \\ s.t \quad & 0 \le k \le \lambda a, \quad n_b \ge 0 \end{aligned} \tag{7}$$

Note that since both choices of labor and capital inputs are made after the realization of productivity shocks ϵ_e, business income is always non-negative, which means business loss is not considered in this economy.[10]

To allow for the impact of borrowing constraints on decisions to become an entrepreneur,[11] we assume that entrepreneurs' capital rental k is limited by a multiple of the collateral, i.e. $k \le \lambda a$.

[10] Any sort of business losses will strengthen the insurance channel provided by progressive taxation, which may strengthen our main results on tax policy analysis in Section 6

[11] See, for instance, Evans and Jovanovic (1989), Quadrini (2000), Hurst and Lusardi (2004), or Cagetti and De Nardi (2006).

3.7 Corporate sector

In reality, a large fraction of firms are not managed by households weighing the cost and benefit of running their own business or working in someone else's company. Therefore, as in Quadrini (2000) and Cagetti and De Nardi (2006), we model a second sector of production populated by a large number of homogeneous firms which we refer to as the non-entrepreneurial, or corporate sector. Firms in this sector are operating a constant returns to scale production technology given by

$$A_C F(K_C, N_C) = A_C K_C^{\xi} N_C^{1-\xi} \tag{8}$$

where A_C is the time-invariant corporate productivity, which will be normalized to 1. K_C, N_C are corporate capital and labor demand, respectively. Outputs produced by corporate and entrepreneurial sectors are perfectly substitutable. Corporate sector capital depreciates at the same rate δ as in the entrepreneurial sector.

The problem of the corporate sector is thus given by

$$\pi_C = \max_{K_C, N_C \geq 0} \{A_C F_C(K_C, N_C) - \omega N_C - (r+\delta)K_C\} \tag{9}$$

subject to the non-negativity constraints of factor demands.

3.8 Recursive problems

Value of retirement $(J^V \leq j \leq J)$ Individuals can claims social security as early as age J^V. Note that retirement is an absorbing state and the value of retirement covers both the voluntary retirement and mandatory retirement ages.

For $j = J$, individuals die with probability 1 at the end of the period, and the value is thus equal to the value of bequest $\mathcal{V}(a)$:

$$V_J^R(a) = \mathcal{V}(a) \quad \forall\ a \tag{10}$$

For $J^V \leq j < J$, once an individual chooses to retire, he or she cannot return the labor market in the future. Individuals thus only make consumption-savings decisions and enjoy leisure of unit 1:

$$\begin{aligned} V_j^R(a) = & \max_{a'} \{u(c,1) + \beta[\psi_j V_{j+1}^R(a') + (1-\psi_j)\mathcal{V}(a')]\} \\ s.t. \quad & a' + c(1+\tau_c) = a(1+r) + z \\ & a' \geq \underline{a} \end{aligned} \tag{P1}$$

Value in normal working ages $(0 < j < J^V)$ During normal working ages, individuals make occupational choice decisions between being a worker or entrepreneur. For $o \in \{W, E\}$

$$
\begin{aligned}
&V_j^o(x_e, a, \epsilon_w, \tilde{\mu}_e, \tilde{\nu}_e, \epsilon_e) = \max_{a',c,l}\{u(c,l;x_e) \\
&+ \beta[\psi_j \max_{o' \in \{W,E\}} \{\mathbb{E}V_{j+1}^W(x_e, a', \epsilon_w', \tilde{\mu}_e', \tilde{\nu}_e', \epsilon_e'), \mathbb{E}V_{j+1}^E(x_e, a', \epsilon_w', \tilde{\mu}_e', \tilde{\nu}_e', \epsilon_e')\} + (1-\psi_j)\mathcal{V}(a')]\} \\
s.t. \quad & a' + c(1+\tau_c) = a(1+r) + (1-\tau_{ss})y_j^o(a, \epsilon_w, \epsilon_e) - T^o(y_j^o) \\
& \tilde{\mu}_e', \tilde{\nu}_e' = \begin{cases} \Pi(\tilde{\mu}_e', \tilde{\nu}_e' | \tilde{\mu}_e, \tilde{\nu}_e, \epsilon_e) & \text{for } \ o = E \\ \tilde{\mu}_e, \tilde{\nu}_e & \text{otherwise} \end{cases} \\
& a' \geq \underline{a}
\end{aligned}
\tag{P2}
$$

where $y_j^o(a, \epsilon_w, \epsilon_e)$ is the total o-occupation pre-tax income. That is, in a given period, an individual with occupation o makes decisions on assets and occupation for next period based on idiosyncratic states. If the individual is an entrepreneur in current period, her belief about the true entrepreneurial productivity will be updated based on the signal ϵ_e realized this period. Workers do not receive entrepreneurial productivity signals and their belief will be the same as the end of last period.

Value of non-retirement in voluntary retirement ages $(J^V \leq j < J^R)$ Starting from J^V, individuals can claim retirement and leave the labor force forever. Individuals form expectations based on the comparison between the value of retirement from problem (P1) and the value of continuing working. The only difference from problem (P2) – the problem during normal working ages – is that individuals have an additional option to retire. The recursive problem is formulates as follows, for $o \in \{W, E\}$

$$
\begin{aligned}
&V_j^o(x_e, a, \epsilon_w, \tilde{\mu}_e, \tilde{\nu}_e, \epsilon_e) = \max_{a',c,l}\{u(c,l;x_e) \\
&+ \beta[\psi_j \max_{o' \in \{W,E,R\}} \{\mathbb{E}V_{j+1}^W(x_e, a', \epsilon_w', \tilde{\mu}_e', \tilde{\nu}_e', \epsilon_e'), \mathbb{E}V_{j+1}^E(x_e, a', \epsilon_w', \tilde{\mu}_e', \tilde{\nu}_e', \epsilon_e'), V_{j+1}^R(a')\} + (1-\psi_j)\mathcal{V}(a')]\}
\end{aligned}
\tag{P3}
$$

subject to the same constraints in problem (P2).

3.9 Stationary competitive equilibrium

An individual with age j is indexed by states $\mathbf{x}_j = (x_e,\ a_j,\ \epsilon_{w,j},\ \tilde{\mu}_{e,j},\ \tilde{\nu}_{e,j},\ \epsilon_{e,j})$. Given a tax structure $\{\tau_c, T^\omega(\cdot), T^b(\cdot), \tau_{ss}\}$ and an initial distributions of workers and entrepreneurs over individual states $\{\Gamma_0^W(\mathbf{x}_0), \Gamma_0^E(\mathbf{x}_0)\}$, a **stationary recursive competitive equilibrium** comprises

- prices $\{w, r\}$ and social security benefits z
- policy and value functions for workers and entrepreneurs
- factors demand of the corporate sector
- distribution of households over idiosyncratic states for both workers and entrepreneurs

such that

1. Given prices, the tax structure, and social security benefits, the policy functions solve individual's problems (P1), (P2), and (P3);
2. The factors demand of the corporate sector solve equation (9);
3. Capital market, labor market, and social security system are cleared;
4. The government budget is balanced every period;
5. The distribution of households is stationary.

The equilibrium concept is standard and fully detailed in the Appendix B.

4 Calibration

In this section, we describe how we parameterize the model in stationary equilibrium. The model is estimated using simulated method of moments to match data of the U.S. economy in the mid 1990s to accommodate the availability of several data sources used in the paper.

4.1 Data sources

We use two primary data sources: (i) PSID between 1977 and 1996 and (ii) PSED Wave I between 1998 and 2004.

4.1.1 PSID

Sample selection Following Heathcote, Perri, and Violante (2010), we focus on the Survey Research Center sample (SRC) of PSID and we choose a sample of heads of households from 1970 to 1997 (corresponding to true years 1969-1996) that includes information on gender, income, age, wealth, self-employment status, and whether the head of a household owns a business.[12] The sample comprises household heads with age from 21 to 75 years old. We

[12] Entry and exit rates of entrepreneurs at annual frequency are only available between 1970 and 1997.

include population above the normal retirement age 65 to take into account the non-trivial fraction of people being entrepreneurs at older ages. We use PSID sample to obtain three sets of moments: (i) the entry rate, exit rate, and entrepreneurs as a share of households over the life cycle, as shown in Section 2; (ii) age profiles of assets and earnings; and (iii) personal income tax schedule.

Earnings The earnings of heads consists of both labor income and business income, which is equal to the labor income of head plus the asset part of business income.[13] Note that the variable on the asset part of business income only applies to individuals who run unincorporated businesses. Unincorporated business owners are not sheltered from the losses of their ventures through limited liability. This means that a head's income can be positive, zero, or negative.

Taxes and transfers We submit PSID household data on incomes, demographics, and geographic information to NBER's TAXSIM program to calculate federal and state level income taxes, as well as deductions.[14] We define pre-government income as the sum of labor income of both head and spouse, private transfer, and net asset income. We define post-government income as pre-government income minus taxes and plus public transfers.

4.1.2 PSED

Survey design As in Section 2, PSED investigates the new business start-up process based on nationally-representative samples of nascent entrepreneurs (NE). There is also a control group (CG) consisting of individuals who are not involved in creating new businesses for comparison with NE. The dataset contains useful information related to business creation including business status, capital structure, legal form, expectations, and performances in terms of sales and employment. It also contains information on demographics, labor market experience, and personality traits for all the individuals in the sample including both NE and CG.

Non-pecuniary utilities and personal traits We rely on survey questions from the PSED to document how personal traits affect the entry into entrepreneurship to discipline the non-pecuniary utilities of being an entrepreneur. Intuitively, someone wants to become an entrepreneur simply for non-pecuniary reasons. We capture this margin via a personal

[13]Labor income of heads is defined as income from wages, salaries, commissions, bonuses, overtime and the labor part of self-employment income. The PSID splits self-employment income into asset and labor components using a 50-50 rule.

[14]More details about TAXSIM can be found in Feenberg and Coutts (1993).

trait called *Love of Business* (LoB). We establish the fact that among all the personal traits that completely describe an individual's personality, only LoB is found to affect the choice of becoming an entrepreneur.

We use Principal Component Analysis (PCA) to summarize the original 25 questions into six key traits, i.e. the Big 5 plus *Love of Business* (LoB),[15] following the procedures used in Lise and Postel-Vinay (2020).[16] The constructed traits scores are normalized to lie in $[0, 1]$. We present the distribution of LoB trait in Figure 6 which we will use to discipline the distribution of LoB states in our model.

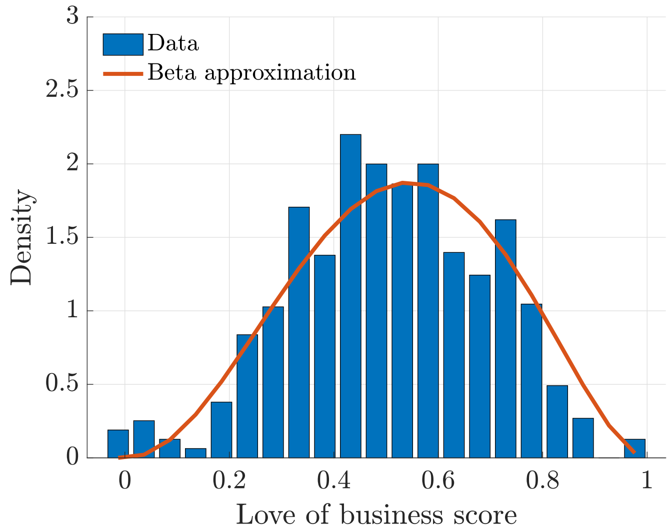

Figure 6: Approximation of love of business score distribution in PSED

Appendix A presents the detailed procedure and properties of the constructed personality traits scores. Consistent with Caspi (2000) and Cobb-Clark and Schurer (2012), we find that all six personality traits appear to be relatively stable over the life cycle starting from around 20 and exhibit no significant difference between genders. More importantly, we show that among the six personal traits, only LoB is found to be significantly different between NE and CG, as shown in Figure A3.

4.1.3 Data limitations

Bhandari et al. (2020) documents that survey data widely used in studies on entrepreneurship are subject to problems of sample representativeness and measurement errors, which are inevitably present in our analysis as well. We lay out several caveats. First, the entrepreneurs considered in our paper should be interpreted as pass-through private business owners who

[15] As emphasized in Hamilton, Papageorge, and Pande (2019), a large literature in psychology use five traits (the Big 5) to completely describe an individual's personality.

[16] Lise and Postel-Vinay (2020) summarizes multiple questions on detailed skills into three main skills.

are subject to personal income taxes as workers. We abstract our paper from corporate business owners for both data and model reasons. The main data source we use PSID oversamples the poor and does not capture the top earners well, thus not suitable to study corporate business owners. From the perspective of model, corporates subject to double taxation at both entity level and firm level, while we only model the tax at the entity level. Ultimately, we believe that our theory of entrepreneurial productivity learning provides a reasonable way to demonstrate the growth of pass-throughs while large corporations should be delineated with more complicated process of business idea generation and different way of financing.[17] Second, PSID does not measure business income well. Our calibration strategy which combines sales data from PSED and income data from PSID potentially provides a more accurate estimate on entrepreneurial productivity process than using income data from PSID only. Third, even though workers and passthrough business owners are subject to the same statutory income tax scheme, they may face different effective tax rates in practice due to two main reasons—(1) different deductions and tax credits claimed; and (2) underreporting and tax evasion.[18] Due to lack of detailed micro data on misreporting, it is hard to obtain reliable estimates of effective tax rates of passthroughs especially that of long time-series. Bhandari and McGrattan (2021) provides estimates on effective tax rates of passthroughs using data of 2007 and shows private business owners face lower effective rates than wage earners. In our paper, we simply assume that workers and entrepreneurs face the same tax schedule and estimate the tax schedule using TAXSIM. Our benchmark tax schedule should thus be interpreted as statutory, while our main results established in Section 6 will not be affected if we use effective rates estimated in Bhandari and McGrattan (2021) instead.

4.2 Functional specification and parameterization

4.2.1 Demographics, preferences, and discounting

A model period is equivalent to one year. Individuals are born at age 21 (model period 1). They have the option to retire voluntarily at age of 62 (model period $J^V = 42$), retire compulsorily at the age of 80 (model period $J^R = 60$), and die with probability 1 at model age 101 (model period $J = 81$). The population growth rate g_n is 0.011 at annual rate and the mortality probability is taken from Bell and Miller (2005).

Individuals have time-separable preferences over consumption and leisure and discount the future with factor β. Individuals derive flow utility from consumption c and leisure l.

[17] See Dyrda and Pugsley (2020) for a model featuring both passthroughs and corporations.

[18] Johns and Slemrod (2010) and Bhandari et al. (2020) report that business income of pass-throughs are subject to a high degree of non-compliance and misreporting.

Both workers and entrepreneurs are endowed with one unit of productive time. Individuals' decisions depend on preferences represented by the following flow utility functional form:

$$\begin{aligned} u(c_j, l_j; x_e) =& \frac{(c_j^{\gamma} l_j^{1-\gamma})^{1-\zeta}}{1-\zeta}, \qquad \gamma \in (0,1), \zeta > 0 \\ l_j =& 1 - (\phi_{w,0} + h_j)\mathbb{I}_{\{h_j>0\}} - g(x_e)\mathbb{I}_{\{o_j=E\}}. \end{aligned} \tag{11}$$

In this utility function, γ is a utility weight of consumption, and ζ determines the risk aversion of the individuals. We set $\zeta = 4$ which is standard in the macro labor literature, and choose β and γ such that the stationary equilibrium of the economy with the benchmark tax system features a capital-output ratio of 2.7 and an average share of time worked of one-third of the time endowment.[19]

For a worker, they split the time endowment between work and leisure. Workers face a discrete choice of four possible levels of weekly hours: $h_j \in [0, 20, 40, 50]$. Leisure l for workers who work zero hours is just equal to one. Workers who work positive hours derive disutility from working hours h and a fixed utility cost of working $\phi_{w,0}$. We choose $\phi_{w,0}$ to match a 70% employment rate in the U.S. for all the population between age 21 and 65.

Non-pecuniary utilities The non-pecuniary motive to be an entrepreneur in our model is manifested as a fixed utility cost of being an entrepreneur, $g(x_e)$ in equation (11), which is a linear function of Love of Business (LoB) state x_e. In order to discipline the distribution of the LoB States x_e, we first generate a distribution of LoB scores across nascent entrepreneurs from our PSED sample. Since the LoB scores are ranged from zero to one by construction, we approximate it to a Beta distribution with two shape parameters equal to 3.2 and 2.8. Finally, we discretize the Beta distribution with seven states for simulation as in Figure 6.

We specify $g(x_e) = \phi_{e,0} + \phi_{e,1} x_e$. The slope parameter $\phi_{e,1}$ captures the differences in the utility cost faced by agents with different LoB states, which is set to match the difference in the mean LoB scores between entrepreneurs and workers in our PSED sample. The idea is that a higher value of $\phi_{e,1}$ means a larger variation in utility costs of being an entrepreneur, thus a larger difference in mean LoB scores between workers and entrepreneurs. The intercept parameter $\phi_{e,0}$ is set to match the share of entrepreneurs in PSID, which is analogous to disciplining the fixed utility cost of workers ϕ_w by the employment rate.

Bequest Following De Nardi (2004) and Lockwood (2018), we use the following bequest utility function:

$$\mathcal{V}(b) = \left(\frac{\phi_b}{1-\phi_b}\right)^{\tilde{\zeta}} \frac{\left(\frac{\phi_b}{1-\phi_b} c_b + b\right)^{1-\tilde{\zeta}}}{1-\zeta} \tag{12}$$

[19] Jones and Pratap (2020) estimate $\zeta = 4.37$ using a panel of diary farms owners.

This functional form together with the parameterization has good numerical properties and easy-to-interpret parameters.[20] $\tilde{\zeta} = 1 - \gamma(\zeta - 1)$ captures the weight on consumption, consistent with flow utility $u(.)$. The parameter $\phi_b \in [0, 1)$ is the marginal propensity to bequeath. Larger values of ϕ_b mean that people leave a larger share of the wealth left over after buying c_b worth of consumption as bequests. The parameter $c_b > 0$ is the threshold consumption level below which people do not leave bequests. We set the threshold parameter c_b to target an amount of \$17000 estimated by Lockwood (2018), and calibrate ϕ_b by to match the moment of bequest as a share of wealth of 60%. We estimate the probability of receiving bequest by age following Cagetti (2003).

4.2.2 Wages, corporate production, and entrepreneurial productivity learning

Wage income process The wage income process consists of four parts—general equilibrium wage rate ω, an age profile of worker productivity, permanent ability types, and idiosyncratic shocks. The age-productivity profile $\{\theta_j\}_{j=1}^{J^R-1}$ is taken from Hansen (1993). Following Conesa, Kitao, and Krueger (2009), we consider two ability types, χ_1 and χ_2, with equal population mass and fixed effects. That is, $\chi_1 = e^{-\sigma_\chi}$ and $\chi_2 = e^{\sigma_\chi}$ such that $E(log(\chi_i)) = 0, var(log(\chi_i)) = \sigma_\chi^2$.

Idiosyncratic shocks of wage income follow a simple AR(1) process with persistence parameter ρ_w and unconditional variance σ_w^2:

$$\log \epsilon_{w,j} = \rho_\omega \log \epsilon_{w,j-1} + \varepsilon_{w,j}, \qquad \varepsilon_w \sim i.i.d.\mathcal{N}(0, \sigma_w^2) \tag{13}$$

We take the parameters from Conesa, Kitao, and Krueger (2009) and approximate the stochastic process with seven discrete states.

Corporate sector production technology The capital share parameter ξ of corporate firms' production function is set to be 0.36 to match the labor income share of corporate sector from the BEA-NIPA. For simplicity, we make the value of the capital share parameter of the entrepreneurial sector equal to that of the corporate sector. The span of control parameter η is set to be 0.79 following Buera, Kaboski, and Shin (2011). Taking the scale of production η into consideration leads to a capital share $\alpha\gamma = 0.28$ for the entrepreneurial sector, which is close to the value used in the macro literature on entrepreneurs (e.g. Buera, Kaboski, and Shin (2011), Cagetti and De Nardi (2006)). The capital depreciation rate is set to be 6% based on the estimates using the BEA fixed asset tables taking both physical capital and BEA-measured intangible capital (or Intellectual Property Products capital) into

[20]See Appendix B for more details.

consideration. Since individuals' wealth accumulation significantly affects whether they are financially constrained or not once they become an entrepreneur, we discipline the collateral parameter λ to target the PSID moment that the ratio of the median wealth held by entrepreneurs to that held by workers is around six.

Entrepreneurial productivity learning process The key parameters of our benchmark model are those that discipline the entrepreneurial productivity learning process $\{\mu_e, \sigma_e^2, \nu_e^2\}$. We jointly calibrate the variance of the distribution of transitory shocks σ_e^2 and the variance of the distribution of the innate ability types ν_e^2 to match the variance of forecast errors in year 1 as in Figure 1(a) and the slope of forecast revisions to forecast errors as in Figure 1(b). The identification comes from the fact that these two moments are separately determined by the *absolute* and the *relative* sizes of σ_e^2 and ν_e^2, as discussed in the Section 3. The mean of the distribution of the innate ability types μ_e determines the level of profits earned by entrepreneurs and is thus chosen to match the ratio of the mean income of entrepreneurs to that of workers.

Based on our calibration, the size of the ex-post risk σ_e^2, 0.50, is greater than the size of the ex-ante risk ν_e^2, 0.37. This renders the learning speed is not that fast. As shown in Figure A12, on average, even after 50 years' labor market experience, the standard deviation of the belief about the innate entrepreneurial ability decreases only by around 30%.

4.2.3 Government policies

Following Bhandari and McGrattan (2021), we set consumption tax rate τ_c to be 0.065. Following Conesa, Kitao, and Krueger (2009), we set payroll tax rate τ_{ss} to be 0.124. Benefit z is determined by the balanced government budget in the equilibrium (see equation (A4) in Appendix B).

Motivated by the fact that the logged after-tax income and logged pre-tax income exhibit roughly a linear relationship in the US data, Benabou (2002) and Heathcote, Storesletten, and Violante (2017) approximate the progressive income tax system with the following nonlinear function:

$$T(y) = y - (1-\kappa_0)(y)^{(1-\kappa_1)} \tag{14}$$

alternatively,

$$ln(y - T(y)) = ln(1-\kappa_0) + (1-\kappa_1)lny \tag{15}$$

where y is the pre-tax income, $T(y)$ is the associated tax liabilities, and $y - T(y)$ is the after-tax income. Equation (14) characterizes the tax function with a level parameter κ_0 and a progressivity parameter κ_1. A tax schedule with $\kappa_1 = 0$ corresponds to a proportional income tax system. As κ_1 increases, the tax system becomes more progressive.

Following Heathcote, Storesletten, and Violante (2017), we recover parameters κ_0 and κ_1 from our PSID sample from an ordinary least squares (OLS) regression using Equation (14). We take income variables from the PSID, which are submitted to the TAXSIM program to obtain tax liabilities and exemptions. In our benchmark estimation, we pool entrepreneurs and workers together and measure pre-tax incomes y as the sum of labor income and self-employment income, as in Section 4.1.1. We obtain $\kappa_0 = 0.0912$ and $\kappa_1 = 0.1416$.

4.3 Model performances

With the baseline parameters in Table 1, we compute an equilibrium of the model and check if our model is able to rationalize salient features aligned with U.S. data.

Entrepreneurship over the life cycle Figure 7 presents the first key result of our paper. Although none of the moments are explicitly targeted, our model can well replicate the life cycle patterns of entry, exit, and the overall share of entrepreneurs in the households. This is the consequence of the interaction between two key elements of the model: asset accumulation with financial friction and reduced uncertainty via learning.

The earlier the uncertainty resolved, the longer periods an entrepreneur shall expect to operate, thus reaping more earnings conditional on they find themselves innately productive. Therefore, agents always want to experiment with entrepreneurship to learn about their innate ability as early as possible. However, due to low asset level when agents are young, it is hard for them to insure against a bad productivity shock, and even with a high shock realization, young agents with insufficient assets will not be able to scale up production to increase earnings because of the collateral constraints. The asset accumulation channel holds up young agents' entry decision. Therefore, the two channels jointly determine that entry age of entrepreneurs peaks at the middle age, which is consistent with our empirical finding in Figure 7. The declining exit rate for people in working age is mainly driven by reduced uncertainty via learning. When people just enter the labor market, they have no information about their true entrepreneurial productivities, so they enter to learn about their abilities. This explains the high exit rate at the early stage of the life cycle. As individuals obtain more information, only productive agents will stay. We also check the life cycle moments that are more directly related to learning, which is the exit rate by business duration, reported in Figure 8(a).

Recurrent entrepreneurial activities We also check whether the distribution of the recurrent entrepreneurial activities implied by the model is consistent with the data. Since

Table 1: Model parameterization

Parameter	Description	Value	Source/Target
Demographics			
J^V	Youngest age to claim retirement	42	Age 62
J^R	Age of mandatory retirement	60	Age 80
J	Age of death	81	Age 101
g_n	Population growth rate	0.011	
$\{\psi_j\}_{j=1,\dots,81}$	Survival probability		Bell and Miller (2005)
Preferences			
ζ	Risk aversion	4	IES = 0.5
γ	Intensity of consumption	0.40	2,000 annual hours for workers
β	Discount factor	1.00	K/Y = 2.7
ϕ_ω	Fixed cost of working	0.25	Employment rate = 0.70
c_b	Threshold consumption level	0.30	\$17000
ϕ_b	Marginal propensity to bequeath	0.95	Bequest as a share of wealth = 0.6
$(\beta_{e,1}, \beta_{e,2})$	Beta distribution: LoB score	(3.2, 2.8)	PSED LoB distribution
$\phi_{e,0}$	Fixed cost of entrep.: intercept	0.60	Share of entrep. in population = 8.8%
$\phi_{e,1}$	Fixed cost of entrep.: slope	–0.09	Diff. in mean LoB: entrep. to worker = 0.10
Entrepreneurial productivity learning process			
μ_e	Mean: innate entrep. prod.	1.25	Mean business to wage income = 1.2
ν_e	Std. dev.: innate entrep. prod.	0.37	Std. dev. of forecasting error = 0.40
σ_e	Std. dev.: i.i.d.shocks	0.50	Slope of forecast revision = 0.62
Wage income			
$\{\theta_j\}_{j=1,\dots,45}$	Age-dependent wage productivity		Hansen (1993)
ρ_w	Wage income shock: persistence	0.98	Conesa, Kitao, and Krueger (2009)
σ_w	Wage income shock: std. dev.	0.17	Conesa, Kitao, and Krueger (2009)
σ_χ	Permanent types dist.: std. dev	0.37	Conesa, Kitao, and Krueger (2009)
Production technology			
ξ	Capital share: corporate	0.36	Corporate labor share from NIPA
α	Capital share: entrepreneurs	0.36	Same as ξ
η	Span of control: entrepreneurs	0.79	Buera, Kaboski, and Shin (2011)
δ	Capital depreciation rate	0.06	BEA fixed asset tables
λ	Collateral parameter	1.50	Median wealth entrep. to worker = 6.0
Government policy			
τ_c	Consumption tax rate	0.065	Bhandari and McGrattan (2021)
τ_{ss}	Payroll tax rate	0.124	Conesa, Kitao, and Krueger (2009)
κ_0	Income tax: level shifter	0.091	PSID estimation
κ_1	Income tax: progressivity	0.142	PSID estimation

our model implicitly assumes that if an entrepreneur choose to exit and become a worker,

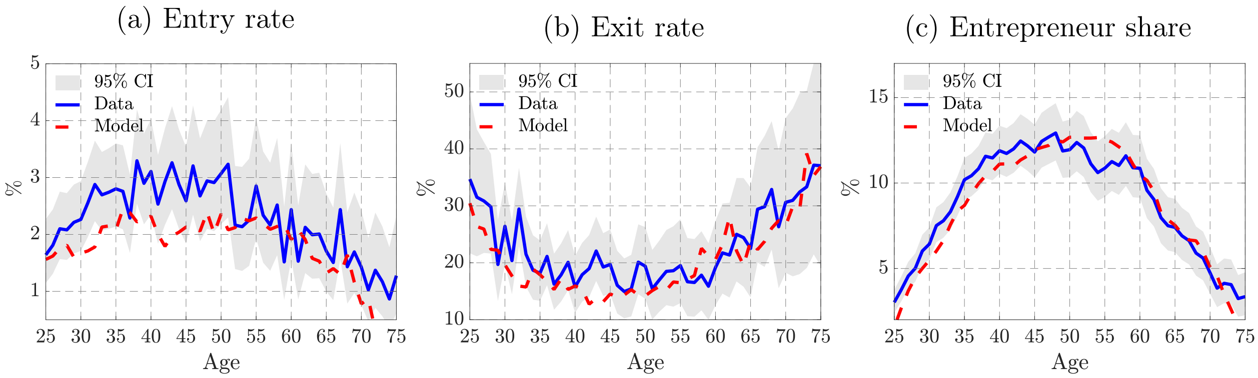

Figure 7: Model fit – entry and exit rates over the life cycle

she will not lose her learning experience on the innate entrepreneurial productivity, which may not necessarily be true in reality, we need to make sure that our assumption is not too extreme. In Figure 8(b), the horizontal axis represents the number of entrepreneurial recurrence where the number one means an individual has been an entrepreneur once during her lifetime in our PSID sample and two means an individual who has been an entrepreneur twice (entering and exiting and entering again) etc., while the vertical axis represents the share of a certain group of individuals in the horizontal axis among all the individuals who have been an entrepreneur at least once. We can see that around 65% of the individuals in the data have only been an entrepreneur once during their lifetime. Our model can well replicate the data.

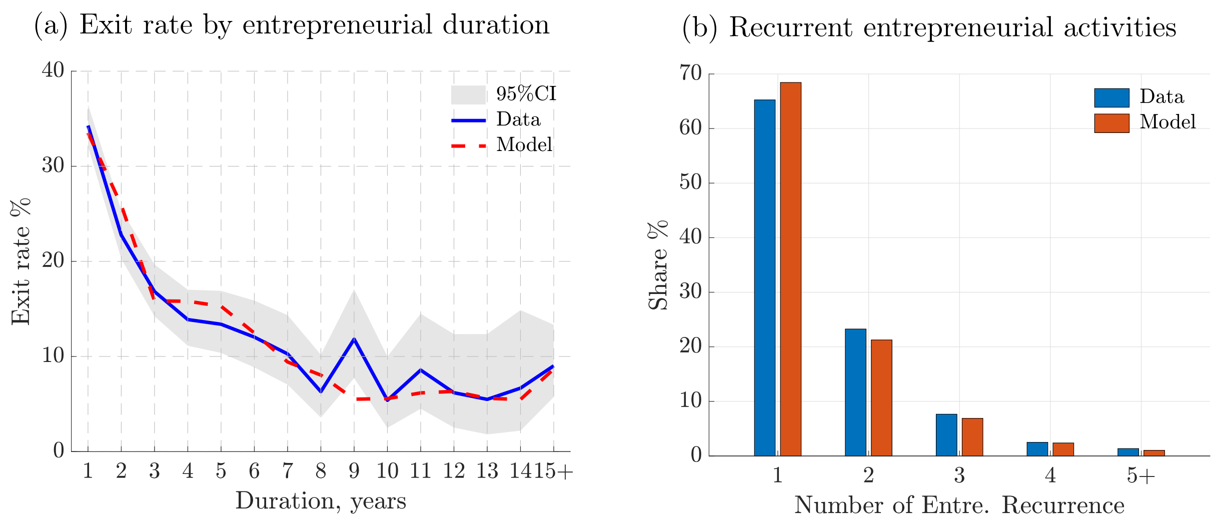

Figure 8: Model fit – exit and recurrence of entrepreneurial activities

Entrepreneurial earnings The existing literature that incorporates productivity learning in a structural model of entrepreneurs (e.g. Dillon and Stanton (2018); Hincapié (2020)) typically rely on moments on earnings of entrepreneurs and workers to identify the learning process, while, in our paper, we use direct evidence on entrepreneurs' expectation formation to discipline the learning process. In Figure 9, we show our model can well replicate the the mean and standard deviation of entrepreneurial earnings by duration.

Figure 9: Model fit – earnings by entrepreneurial duration

Income and wealth distribution Our calibrated model can match both the income and wealth distribution well as in Cagetti and De Nardi (2006). The results are reported in Table 2.

For other key moments including the first-time entrants as a share of the population, firm size distribution in entrepreneurial sector, and national accounts, the model implied moments are also aligned with data well. We report the results in more details in Appendix B.

5 The value of learning and the cost of uncertainty

We use the model to explore how the value of learning varied by age as well as quantify the cost of the uncertainty about the innate entrepreneurial ability by comparing a case of perfect information where individuals perfectly know their innate productivity upon entering the labor market.

5.1 The value of learning

We measure the value of learning in terms of three objective moments: (1) aggregate entrepreneur share across ages; (2) discounted lifetime business income; and (3) discounted lifetime total income (i.e. the sum of wage income, business income, and asset income ra).

Table 2: Model fit – income and wealth distribution

	Benchmark	Data
Gini coefficient		
Income – all	0.54	0.55
Income – worker	0.29	0.38
Income – entrepreneur	0.59	0.66
Wealth – all	0.64	0.85
Income/wealth ratios: entrepreneur to worker		
Income – median	1.60	1.30
Income – mean	2.60	2.50
Wealth – median	5.90	6.00
Fraction of entrepreneurs in wealth percentiles		
Top 1%	0.56	0.54
Top 5%	0.48	0.39
Top 10%	0.31	0.32
Top 20%	0.22	0.22

The exercise we conduct is that we check the deviation in objective moments from the benchmark economy if we do not allow agents to update their beliefs about the innate ability at a specific age. In this way, we would be able to know whether the age of becoming an entrepreneur matters in the presence of uncertainty about the innate entrepreneurial ability since in the benchmark model, only when an agent choose to become an entrepreneur first can she obtain signals on her true productivity, thus able to update beliefs accordingly.

As we can see from Figure 10, when agents know that they are not able to learn at a certain age, they are less likely to be an entrepreneur, even at older ages, compared to the benchmark economy. Consequently, the discounted lifetime business income also becomes less for all age groups. So does the discounted lifetime total income due to worsened occupation allocation. This implies that there is always a positive value of learning about the innate ability and reducing the uncertainty on it as well.

Overall, the value of learning is monotonically decreasing in age except for the very young in terms of the deviation of entrepreneur share. The reason is that young agents, who possesses low amount of assets, do not gain as much from learning since their earnings are constrained by financial friction even if they find themselves innately productive and they

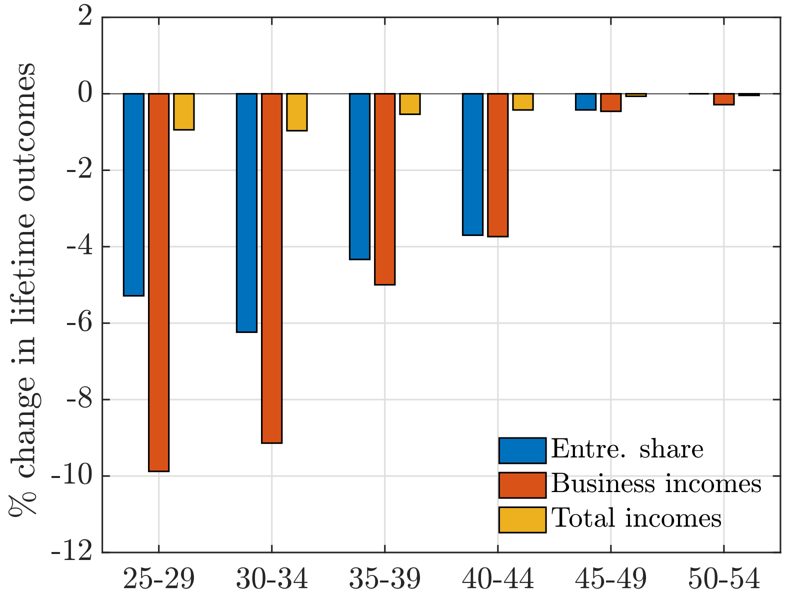

Figure 10: Value of learning

are in lack of enough assets to smooth consumption with low productivity shock realizations. As they age, the financial constraint is gradually relaxed, the horizon effect dominates so that the value of learning is strictly decreasing in age. The value of learning in terms of aggregate entrepreneur share peaks between age 30 and 34. This means if agents with age 30 to 34 do not learn about their innate productivity, the aggregate entrepreneur share across ages would decrease from the benchmark 9% to the counterfactual 8.4%. In other words, the timing of becoming an entrepreneur makes a lot difference. The younger you become an entrepreneur to learn about your innate type, the earlier the uncertainty can be resolved, and consequently, the better the occupation allocation, the higher the aggregate entrepreneur share, and the more the lifetime income can be reaped cross-sectionally.

5.2 The cost of uncertainty

To quantify the cost of information friction in the sense that agents do not know their innate entrepreneurial ability upon entering the labor market, we compare our benchmark economy with such an information friction and learning with a case of perfect information. The only deviation of the perfect information case from the benchmark is that individuals already know their true entrepreneurial ability before entering the labor market. After they decide to be an entrepreneur, there will still be transitory shocks realized to their innate productivity, which are essentially the productivity given which the output is produced. Thus, the case of perfect information can be easily nested by our benchmark model.

We check the lifetime outcomes by innate entrepreneurial ability types and report the results in Table 3. More specifically, we consider seven productivity levels, from the -3 standard deviation from the mean to the +3 standard deviation. We look at three lifetime variables for each type: (1) entrepreneur share; (2) the share of business income in total income; and (3) the total income where that of the lowest type is normalized to be one. We then compare the two cases. First, it is straightforward to see that regardless of cases, the chance to be an entrepreneur and the corresponding share of business income in total income and the total income are all increasing in the entrepreneurial ability type. Second, comparing the two cases, we can see that in the case of perfect information, only individuals with high innate entrepreneurial ability choose to be an entrepreneur, while in our benchmark case, even very low type agents have the chance to choose to an entrepreneur. Third, we are able to get some sense of the cost of the information friction by comparing our benchmark case with the perfect information one. Switching to the case without information friction dramatically improves the occupation allocation by raising the chance of the agents with high entrepreneurial productivity (above the mean) to be an entrepreneur during their lifetime as well as the share of business income in their total incomes. For example, without information friction, the chance of individuals with the highest type (+3 standard deviation) to be an entrepreneur during their lifetime increases from 0.39 to 0.94, and most of the income, i.e. 99%, comes from business income rather than labor income. This also implies that the value of learning is higher for agents with relatively high entrepreneurial productivity. A key policy implication from this result is that in the presence of information friction, potential entrepreneurs with high productivity benefit disproportionately from any policies encouraging people entering to learn to discover their innate entrepreneurial ability.

Table 3: Lifetime outcomes by innate entrepreneur ability types

Types	-3 sd	-2 sd	-1 sd	0 sd	+1 sd	+2 sd	+3 sd
Benchmark with information friction and learning							
Lifetime entrepreneur share	0.01	0.01	0.02	0.04	0.14	0.34	0.39
Lifetime y^b in total y	0.00	0.00	0.01	0.02	0.12	0.40	0.61
Lifetime incomes (normalized)	1.00	1.00	1.00	1.00	1.06	1.35	1.87
Perfect information (PI)							
Lifetime entrepreneur share	0.00	0.00	0.00	0.00	0.12	0.71	0.94
Lifetime y^b in total y	0.00	0.00	0.00	0.00	0.09	0.64	0.99
Lifetime incomes(normalized)	1.00	1.00	1.00	1.00	1.04	1.48	2.56

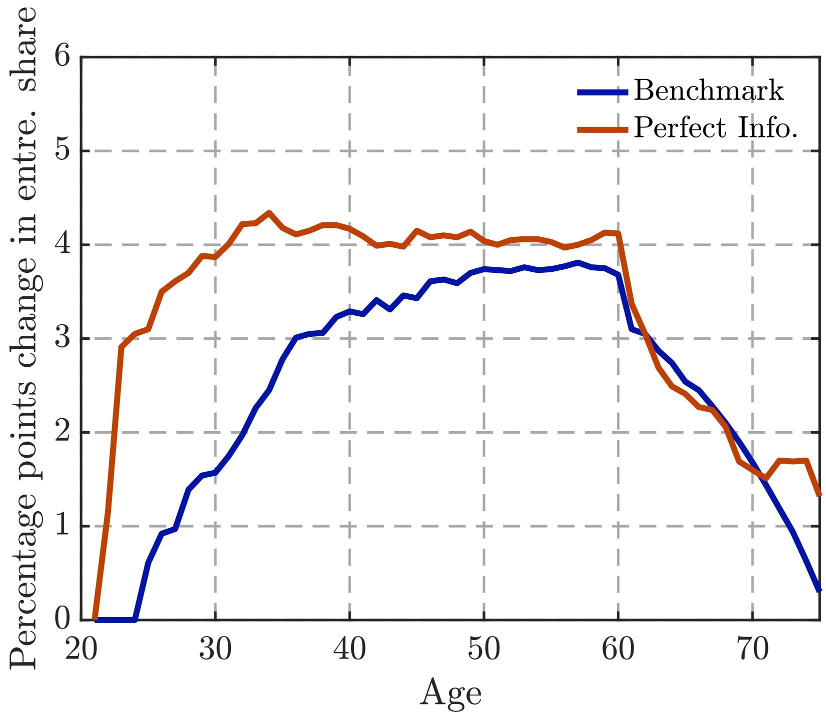

Figure 11: Level change in entrepreneur share when the collateral constraint is relaxed

5.3 How important is asset accumulation channel?

Since both entrepreneurial productivity learning in the presence of information friction and asset accumulation in the presence of financial friction both affect the entrepreneurial choice, we should get some sense on how important the asset accumulation channel is to better understand the role of learning in shaping the entrepreneurship over the life cycle. We conduct the exercise by raising the value of the collateral parameter λ from the calibrated 1.5 to 2.0, which means the share of their own's assets that entrepreneurs are able to borrow up to to finance the capital rental increases from 50% to 100%. The insights behind this exercise is that the collateral requirement λ is a key parameter largely influencing the saving motive.

We plot the results in Figure 11 where we can see that in the benchmark case, relaxing the borrowing constraint does not raise much the entrepreneur share of the young, while in the case of perfect information where there is only asset accumulation channel, the share of the young entrepreneurs dramatically increases. This indicates that in our benchmark economy with the current calibrated parameters, uncertainty on true types together with entrepreneurial productivity learning play a more important role in driving the life cycle dynamics of entrepreneurship than asset accumulation.

6 Tax policy experiments

Equipped with a model incorporating the lifecycle learning dynamics that is consistent with salient features from the micro and macro data, we proceed to deliver the key message on tax policies aimed at promoting entrepreneurship. We first simulate a revenue-neutral flat business income tax reform and contrast it to the benchmark progressive taxation scheme. We then compare the results with the case of perfect information to highlight the role of information friction and entrepreneurial productivity learning in generating the dynamic persistent effects of tax policies on entrepreneurship.

We start by fixing the wage income tax schedule for workers to the benchmark but changing the business income tax schedule by applying a constant flat rate to all the private business income. We focus on steady state comparisons. We vary the level of flat rates until we find a rate that generates the same level of government revenue as that of the benchmark. We find that a 20% flat business tax rate achieves the maximum revenue among the class of flat rate schedules, and also roughly revenue-neutral to the benchmark. The result that we hardly find a flat rate that dominates the current progressive tax system challenges the conventional view that a flat tax reform may be revenue-improving since it favors high productivity entrepreneurs.

We report the lifecycle results in Table 4. It is not surprising to see that the share of entrepreneurs in the 25-34 age group declines since agents in that group assume higher tax burden (as the average tax rate (ATR) faced by them increases by 29.5%). However, for older age groups, even though the tax burden imposed to them now becomes smaller, the share of people who are entrepreneurs in those groups declines even more compared to the youngest age group, mainly driven by the dynamic persistent effect of learning. The reason is that if less people become entrepreneurs to discover their innate productivity when they are young, they will not become entrepreneurs when they are older since the vale of learning is monotonically decreasing in age as Figure 10 shows. Moreover, entrepreneurial activities in terms of output shift toward older and wealthy people. The average firm size in the entrepreneurial sector also becomes larger.

Next, we check the distributional effects of the flat business income tax reform across innate entrepreneurial ability types. We still consider seven productivity levels, from the -3 standard deviation from the mean to the +3 standard deviation. We consider the percentage change in lifetime outcomes in terms of entrepreneur share, business income, and total income given each innate productivity level. As in Figure 13, it is those with relatively high innate entrepreneurial ability (above mean) lose more from the flat tax reform. This is because the flax tax discourage the young agents from entering to discover their entrepreneurial talents,

Age	Entre. Share	ATR	Assets	Output
25-34	–33.6	29.4	5.0	4.7
35-44	–35.7	–1.7	14.2	10.4
45-54	–35.0	–9.0	17.9	11.3
55-64	–38.0	–16.0	26.0	16.4
65-74	–43.0	–20.0	36.9	22.6

Table 4: Impacts under flat tax, % change relative to benchmark

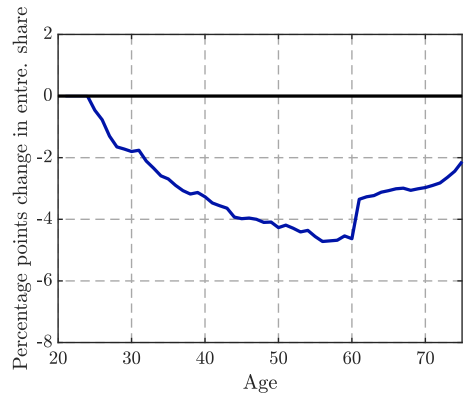

Figure 12: Dynamic lifecycle effects

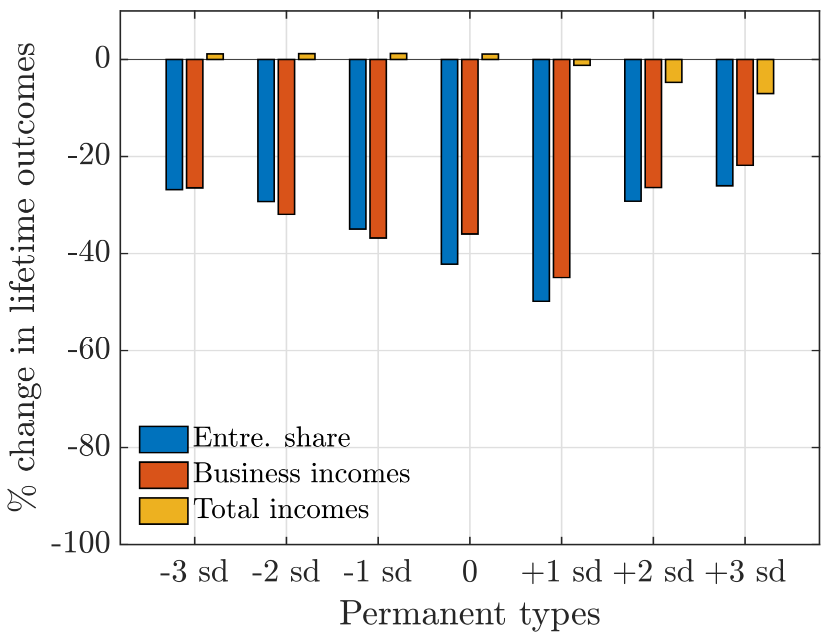

Figure 13: Distributional effects of the flat tax reform across innate ability types

which only has negative impacts on those with high innate productivity since low ability type agents will not become an entrepreneur anyway, regardless of whether they learn or not. This result strikingly differs from the implications of a more standard occupation choice model with infinite horizon a la Cagetti and De Nardi (2006); Evans and Jovanovic (1989) as well as the conventional view that high productivity high income entrepreneurs should benefit more from a revenue-neutral flat tax reform. The key deviations of our model from the standard ones are lifecycle and entrepreneurial productivity learning, which puts the entry margin at the center of tax policies aimed at promoting entrepreneurship: incumbent successful entrepreneurs do prefer flat tax, but taking the entire lifecycle dynamics into consideration, flat tax prevents those with high innate entrepreneurial ability from being an entrepreneur

Table 5: % change under flat tax reform, comparing with prefect information

Age	Entre. share	Ave. tax rates	Ave. assets	Ave. output
Benchmark with information friction and learning				
25-34	–33.6	29.4	5.0	4.7
35-44	–35.7	–1.7	14.2	10.4
45-54	–35.0	–9.0	17.9	11.3
55-64	–38.0	–16.0	26.0	16.4
Perfect information (PI)				
25-34	–36.6	36.3	14.0	12.8
35-44	–19.8	3.7	7.2	7.5
45-54	–14.8	-6.0	10.7	8.8
55-64	–13.3	-11.5	15.5	11.0

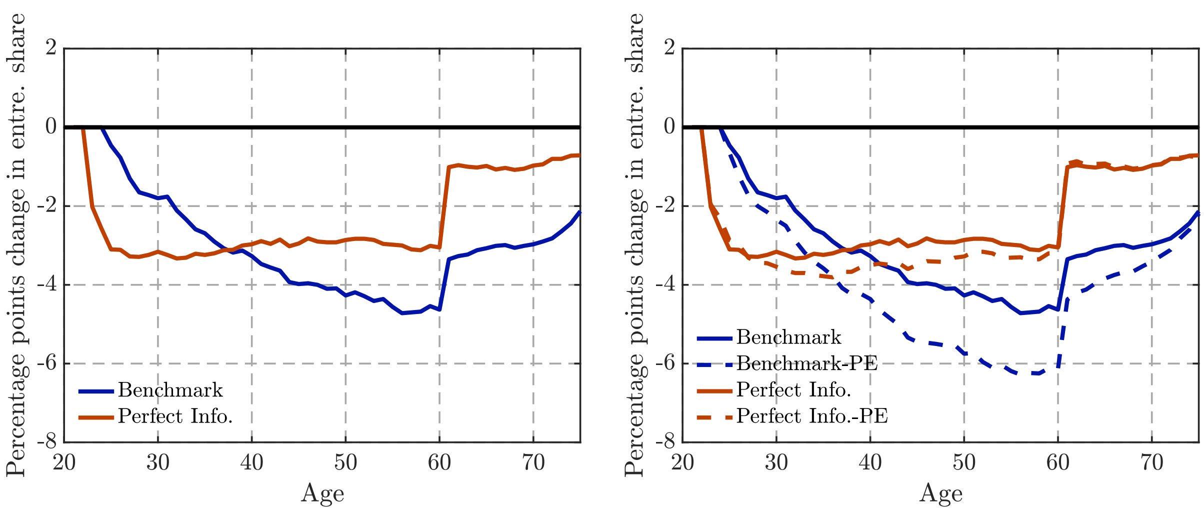

Figure 14: Dynamic lifecycle effects, comparing with perfect information

to discover their entrepreneurial talents. As a result, those highly successful entrepreneurs may not even become an entrepreneur during their lifetime due to the tax reform.

Overall, under the revenue-neutral flat tax reform, the aggregate entrepreneur share declines from 9.0% to 6.0%. The average marginal tax rate decreases from 26.0% to 24.1%. The equilibrium wage rate declines by 1.1%. The aggregate output (the sum of entrepreneurial output and corporate output) declines by 1.6% since now less output is produced by entrepreneurial sector. The reason is that those with high innate productivity who should have become an entrepreneur under the benchmark progressive tax scheme now never become an entrepreneur or spend less time being an entrepreneur and producing during their lifetime under the flat tax reform.The overall welfare is worsened as the consumption-equivalent welfare declines by 2.0%.

Finally, we compare the impacts of the flat tax reform in our benchmark model with an alternative framework with prefect information as in Section 5. We report the results in Table 5 and Figure 14. In the case of perfect information, there is little dynamic persistent effect in the sense that only the share of entrepreneurs in the young age group declines a lot, and the magnitude of the decline become smaller and smaller with older age groups. The logic behind is that when agents perfectly know their innate entrepreneurial ability before they enter the labor market, it is not so important for them to enter to become an entrepreneur at a younger age since they do not need to learn about their productivity as in the benchmark model. This shows the importance of incorporating information friction and entrepreneurial productivity learning into the model used to evaluate tax policies regarding entrepreneurship, not just because we do observe large uncertainty faced by entrants and their belief updating process about their business performances in the data, but also because it leads to very different policy implications. In addition, we find that partial equilibrium strengthens the impacts of the flat tax reform in both cases as the right panel of Figure 14 illustrates.

7 Conclusions

In this paper, we use novel subjective belief micro data showing entrepreneurs face non-trivial uncertainty upon entry and they do learn from their past experience to predict their future business performances. We develop a quantitative life cycle model that incorporates the uncertainty and entrepreneurial learning process, disciplined by data. We show the lifecycle learning dynamics matter a lot for quantitative results of the impacts of personal income tax policy on entrepreneurship. The conventional view is that a flat tax reform should favor high income high productivity entrepreneurs relative to a comparable progressive taxation scheme. Our results highlight the entry margin by delivering the key message that without entering to learn to discover the entrepreneurial aptitudes, those highly successful entrepreneurs may never show up. Since progressive tax favors the young by imposing less tax burden and providing more insurance, it eventually also benefits those incumbent old successful entrepreneurs. A main policy implication is hence that entrepreneurship-boosting policies should prioritize the young.

Furthermore, our results provide an answer to the question why the government wants to boost entrepreneurial activities through policies. In a world with high uncertainty faced by potential entrant entrepreneurs where people can experiment with entrepreneurship to reduce the uncertainty endogenously, promoting entrepreneurship essentially means promoting activities contributed by those highly productive entrepreneurs since it resolves uncertainty and improve occupation allocation by putting the right people in the right position.

The key findings of our paper has broad implications and also present directions for future research and policy design. Empirically, the dynamic effect over life cycle complicates identifying the causal relationship between tax progressivity and entrepreneurship across time since reducing tax progressivity to boost the incumbent entrepreneurs now might be at the cost of sacrificing the entrepreneurs of future generations. Theoretically, our framework can also potentially contribute to the hot debate on the sources of secularly declining entrepreneurship in the U.S. in the recent three decades. Different sources may suggest different policy implications. For example, from the perspective of the model in Salgado (2020), the decline in entrepreneurship is an efficient consequence of technological improvement, which should not be a cause for concern. However, viewed through the lens of our framework, if a large-scale policy change or increased uncertainty induce too little entry of the young entrepreneurs, or any macro shocks, e.g. the Great Recession or Covid-19, hit the young disproportionately harshly, this should receive more attention from the government and policy makers due to the persistent dynamic effect of the learning mechanism over the life cycle emphasized in our paper. We leave a more thorough and rigorous analysis of these issues for future research.

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Online Appendix for
Personal Income Taxation and Entrepreneurship

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A Data and measurement

A.1 PSED

We use PSED-I (1998-2004) where there are 590 Nascent Entrepreneurs (NE) and 227 people in Controlled Group (CG) are surveyed. Variables related to businesses include business status, capital structure, legal form, expectations, and performances (sales/employment).

To be considered as a NE, individuals need to satisfy the following four criteria. First, the individual had to currently consider himself or herself as involved in the firm creation process. Second, he or she had to have engaged in some business startup activity in the past 12 months. Third, the individual had to expect to own all or part of the new firm being created. Fourth, the initiative, at the time of the initial screening survey, could not have progressed to the point that it could have been considered an operating business.

Key Features of NEs in PSED In terms of legal forms, more than 84% are passthroughs. 50% of NE go with Sole Proprietorships, 20% go with Partnerships, 14% go with S-corp or LLC, 11% go with C-corp, 5% undecided. Regarding whether NEs are attached to paid jobs, about half of them have a paid job (partime or fulltime). 31% of men and 25% of women work full time on their new businesses (>= 35 hrs per week). Large majority of both sexes work for a paid job: Of the 70% of men working for pay, 55% did so full time. The analogous statistics for women are 62% and 39%. In terms of business size operated by NEs, around 40% of men and 50% of women choose to be "merely" self-employed, while the rest expect to become employers over the first five years of operation. As for the industrial choice, a large fraction of the men (35%) is starting a business in Health, Education, and Social services. Among the female NE this is also a strong category (20%). Retail and Restaurants account for 28% of the men and 45% of the women. 15% of the women and 8% of the men chose manufacturing.

Expectation Formation and Learning The learning process is captured by how forecast revision on a business' performance depends on the corresponding forecast error. We rely

Table A1: Summary statistics of sales in PSED

	Mean	25%	Median	75%	Max	Std. Dev.	Skewness	Frac. zero sales	Exit rate
Expected sales in wave 1 ($1000), conditional on entry									
Year 1	214	10	30	100	10,000	823	9.22	0.03	
Year 5	1,789	10	100	350	80,000	7,401	7.40	0.01	
Realized sales in following-up waves ($1000)									
Wave2	241	5	25	90	10,000	1,004	7.34	0.04	0.50
Wave3	508	10	25	185	25,000	2,817	8.38	0.03	0.16
Wave4	887	11	50	200	45,000	5,502	7.87	0.06	–

(a) Sales (b) Employment (c) Correlation

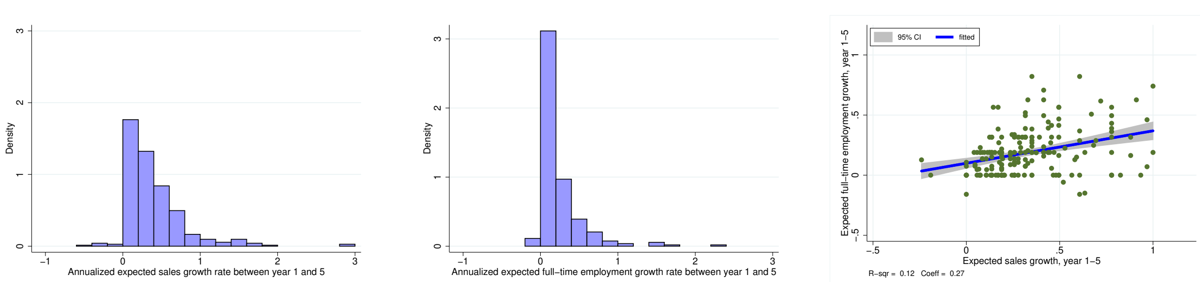

Figure A1: Distribution of forecasts in PSED

(a) Forecasts (b) Realizations

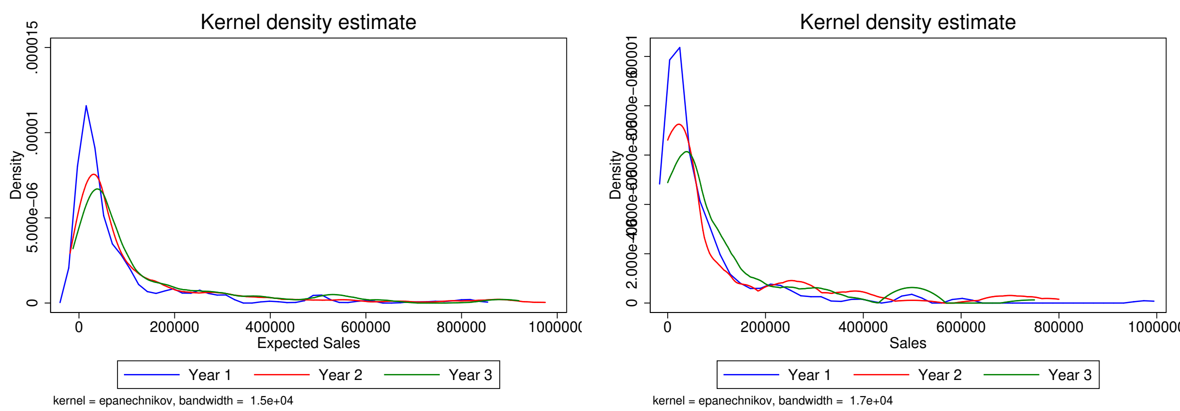

Figure A2: Expected and realized sales by wave

on the following questions from PSED I to measure forecast errors and forecast revision. Respondents in Wave 1 of PSED I report (1) *We would like to ask about your expectations regarding the future of this new firm. First, what would you expect the total sales, revenues, or fees to be in the first full year of operation?* (2) *And what about in the FIFTH year?*. Respondents in Wave 2-4 report (1) *What sales or revenue do you expect in the (current financial year/first full year of operation)?* [21] (2) *What annual sales or income would you expect for the firm FIVE years after the first full year of sales?* (3) *What annual sales or income would you expect for the firm TEN years after the first full year of sales?* This means we have (1) forecast data on sales for period 1 and 5 in period 0, (2) realized sales in period 1, 2, 3, and (3) forecast data on sales for period 5 and 10 in period 1,2,3.

Summarize survey questions to personality traits We use Principal Component Analysis to summarize the original 25 questions into several key traits. The construction follows Lise and Postel-Vinay (2020), which summarize multiple questions on detailed skills into three main skills. Consider number n types of main traits, the construction method is as follows:

1. Run PCA on PSED questions and keep the first n principal components;
2. Recover traits indices by recombining predicted principal components in such a way that they satisfy n certain exclusion restrictions;

[21] Since this question asks about sales/revenue in the current financial year, we regard the answer to this question as the realized sales in that year. To make this approximation solid, we only keep NE that have started operating businesses.

3. Rescale the constructed traits to lie in [0,1].[22]

Besides the five traits considered by Hamilton, Papageorge, and Pande (2019), we additionally consider a general trait for running a business.[23] This is to isolate the preference solely for doing business, which is orthogonal to the general OCEAN traits such as risk-taking, social activities, etc.. The restrictions we consider are the questions in column 'Restriction' of Table A2 only reflect the corresponding traits.

Table A2: Correspondence between "OCEAN" and survey questions

Personality traits	Description	Restriction
Love of business	general love of business	QL1d
Openness to experience	inventive/curious vs. consistent/cautious	QL1q
Conscientiousness	efficient/organized vs. extravagant/careless	QL1b
Extraversion	outgoing/energetic vs. solitary/reserved	QL1h
Agreeableness	friendly/compassionate vs. critical/rational	QL1x
Neuroticism	sensitive/nervous vs. resilient/confident	QL1i

Correlations between traits Table A3 reports the correlation between the constructed personality traits.

Table A3: Correlations between traits

	LoB	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Love of Business	1.0000					
Openness	0.3606	1.0000				
Conscientiousness	0.3237	0.3368	1.0000			
Extraversion	0.1182	0.0056	0.3695	1.0000		
Agreeableness	0.3206	0.5560	0.2088	0.6670	1.0000	
Neuroticism	0.2347	0.6973	0.6665	0.6044	0.8184	1.0000

Table A4 describes differences in the constructed personality traits between men and women and between different age groups. Men have significantly higher scores in openness traits and lower scores in extraversion. Older individuals have significantly higher scores in conscientious trait. All other comparisons are not statistically significant. In particular, the love of business trait does not differ by gender or age.

Note that we are not the first to use the data from PSED to document empirical facts related to non-pecuniary benefits that determines the entry of entrepreneurship. Hurst and

[22] Technical details are referred to the orginal paper of Lise and Postel-Vinay (2020).

[23] More details on "OCEAN" can be found on https://en.wikipedia.org/wiki/Big_Five_personality_traits.

Table A4: Comparison of personality traits by gender and age

	By gender			By age		
	Men	Women	p-value	Age < 40	Age ≥ 40	p-value
Love of Business	0.5742	0.5749	0.9538	0.5727	0.5774	0.7189
	(0.0086)	(0.0085)		(0.0088)	(0.0094)	
Openness	0.5016	0.4685	0.0018	0.4823	0.4871	0.6694
	(0.0078)	(0.0072)		(0.0075)	(0.0083)	
Conscientiousness	0.6021	0.6237	0.0410	0.6250	0.6006	0.0311
	(0.0074)	(0.0075)		(0.0083)	(0.0076)	
Extraversion	0.5623	0.6117	0.0000	0.5847	0.5876	0.7984
	(0.0071)	(0.0072)		(0.0078)	(0.0079)	
Agreeableness	0.6203	0.6237	0.7123	0.6174	0.6270	0.3297
	(0.0065)	(0.0066)		(0.0067)	(0.0072)	
Neuroticism	0.5912	0.5946	0.7235	0.5945	0.5908	0.7106
	(0.0063)	(0.0067)		(0.0069)	(0.0071)	
Sample size	379	395		337	337	

Note: standard deviation in parenthesis

Pugsley (2011) also use PSED and show that the median small business reports starting their business for non-pecuniary reasons. However, their approach is different from ours. They rely on the question *"Why do [or did] you want to start this new business?"*. They took the raw responses to the question and created five broad categories of their own including non-pecuniary reasons and reasons related to the generation of income. The main responses in the non-pecuniary category include "want to be my own boss," "flexibility/set own hours," "work from home," and "enjoy work, have passion for it/ hobby." They find that roughly 50 percent of all respondents reported non-pecuniary benefits as being one of the primary reasons they started their business. We see the results generated using our approach complementary to theirs, and the biggest advantage of our approach is that we can generate a distribution of Love of Business characteristic, which can be used to discipline the non-pecuniary utility in our structural model.

Personality traits and entrepreneurship We plot the distribution of scores of the six personal traits for two groups of individuals in our sample—nascent entrepreneurs and workers (control group). As shown in Figure A3, only the distribution of Love of Business scores exhibit significant difference between the two groups of people.

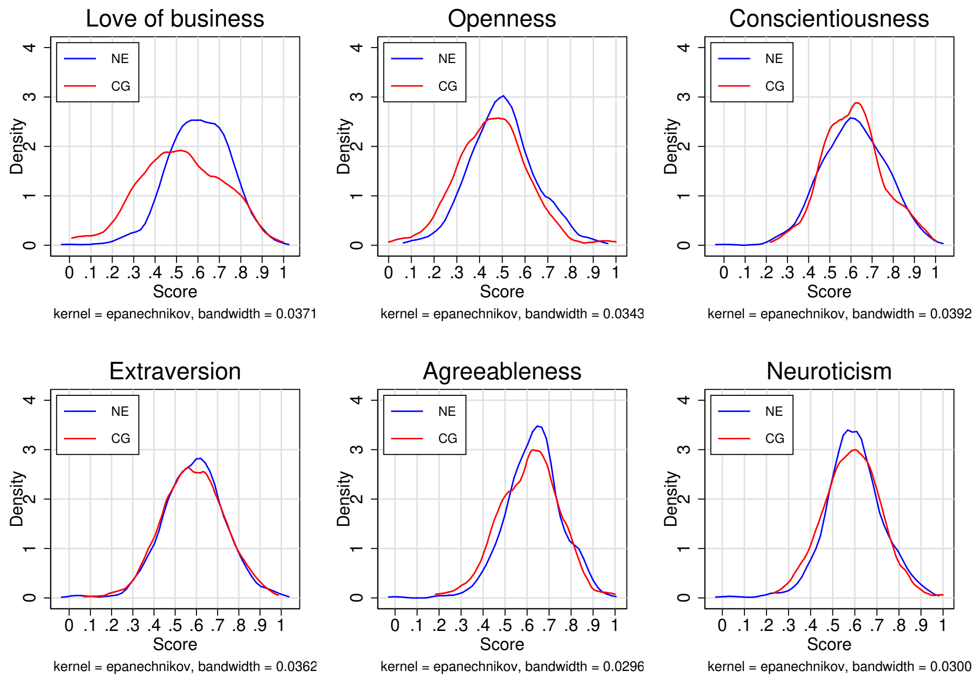

Figure A3: Distribution of scores of personal traits

A.2 PSID

The PSID sample used for studying the life-cycle behavior of entrepreneurs was generated following Heathcote, Perri, and Violante (2010) in general. From the raw data, we extract a sample of heads of households from the SRC sample based on the waves from 1970 to 1997. All monetary variables (income and wealth) are deflated using the Personal Consumption Expenditure index (PCE) and expressed in 2010 dollars. The baseline sample considers households whose head is between 21 and 65 years old, both ends included. We report summary statistics of the sample in Table A5.

Definition of "head" The head of the family unit (FU) must be at least 16 years old, and the person with the most financial responsibility in the FU. If this person is female and she has a husband in the FU, then he is designated as head. If she has a boyfriend with whom she has been living for at least one year, then he is head. However, if she has 1) a husband or a boyfriend who is incapacitated and unable to fulfill the functions of head, 2) a boyfriend who has been living in the FU for less than a year, 3) no husband/boyfriend, then the FU will have a female head. A new head is selected if last year's head moved out of the household unit, died or became incapacitated, or if a single female head has gotten married. Also, if the family is a split-off family (hence a new family unit in the sample), then a new

Table A5: Summary statistics (PSID sample)

	Wage Workers	Entrepreneurs	Labor Force	Total
Obs. per year	2,284	261	2,690	2,994
Age (mean)	38.1	43.0	38.4	39.6
Men (%)	83.4	94.6	83.7	81.4
College or above (%)	27.2	36.1	27.3	26.0
White (%)	89.7	96.0	89.8	89.1
Income (mean, 2010$)	49,357	74,778	50,135	45,882
Wealth (mean, 2010$)	153,164	688,013	206,887	206,294

Note: The table reports statistics of a sample of heads of households between 21 and 65 years old. Each statistic is the sample average across all the survey waves between 1970 and 1997. Entrepreneurs are defined as self-employed business owners. All monetary values are deflated by the PCE index and expressed in 2010 US dollars.

head is chosen.

Samples In this paper, we only consider SRC sample (i.e. id68 <= 3000).

Top-coding and bracketed variables We deal with top-coded observations by assuming the underlying distribution for each component of income is Pareto, and by forecasting the mean value for top-coded observations by extrapolating a Pareto density fitted to the non-top-coded upper end of the observed distribution.

In some of the early waves, a number of income measures were bracketed. For these variables, we use the midpoint of each bracket, and 1.5× the top-coded thresholds for observations in the top bracket.

Variable definitions In the PSID all the questions are retrospective, i.e., variables in survey—year t refer to calendar year $t-1$. The interview is usually conducted around March. When variables were not defined consistently across years (for example employment status was categorized differently in different years), the variables were recoded based on their original (and less detailed) coding, so as to be consistent across years.

Income and earnings: Labor income of heads is defined as income from wages, salaries, commissions, bonuses, overtime and the labor part of self-employment income. The PSID splits self-employment income into asset and labor components using a 50-50 rule.

The earnings of heads consists of both labor income and business income, which is equal to the labor income of head plus the asset part of business income. Note that the variable on the asset part of business income only applies to individuals who runs unincorporated businesses.

Unincorporated business owners are not sheltered from the losses of their ventures through limited liability. This means that a head's income can be positive, zero, or negative.

Wealth: The measure of wealth is the variable WEALTH2, which is available in specific waves of PSID. This variable is constructed as sum of values of several asset types (family farm business, family accounts, assets, stocks, houses, and other real estate etc.) net of debt value.

Annual hours of work is defined as the sum of annual hours worked on the main job, on extra jobs, plus annual hours of overtime. It is computed by the PSID using information on usual hours worked per week and the number of actual weeks worked in the last year.

Labor force: a household head is considered in the labor force if her employment status is either "Working now", "Only temporarily laid off, sick leave or maternity leave", or "Looking for work, unemployed".

Entrepreneur: The PSID provides several questions that can be used to classify individuals' entrepreneurial status. In our analysis, we use two of these questions. The first question is "Did you (or anyone else in the family there) own a business at any time in (year) or have a financial interest in any business enterprise?". The second one is "On your main job, are you (head) self-employed, or are you employed by someone else?". An individual is defined as an entrepreneur if her answer to both questions are "yes".

For the definition of entrepreneurship, there are two major strands of literature to follow. The first strand of literature (e.g. Decker et al. (2014b), Haltiwanger, Jarmin, and Miranda (2012)) uses firm-level data or establishment-level data to measure it and define entrepreneurs as a particular type of firms based on their age and size (in terms of number of employees). Since available government datasets on the U.S. firms do not have a specific entry for "entrepreneurs." but have traditionally contained information about the size and age of firms, some observers have written or spoken as if small and young businesses are synonymous with entrepreneurs. We also notice that there are several recent papers defining entrepreneurship based on the legal form of the business organizations (e.g. Bhandari and McGrattan (2021), Dyrda and Pugsley (2020)). For example, Dyrda and Pugsley (2020) defines entrepreneurial income as the income from pass-through entities (i.e. sole proprietorships, partnerships, and S corporate firms). The second strand of literature (e.g. Quadrini (2000), Cagetti and De Nardi (2006)) uses household-level data such as PSID and SCF and define entrepreneurs as a type of households based on whether they own a business or are self-employed. Even among papers which use household-level data to define entrepreneurs, there is little consensus about which households or individuals should be classified as such. For example, Evans and Leighton (1989) considers entrepreneurs as those that are self-employed, Hurst and Lusardi (2004) considers all those households that own a business, whereas Gentry and Hubbard (2004) defines entrepreneurs as business owners with a total market value of businesses \$5,000 or more. Quadrini (2000) considers individuals that must be both business owners and self-employed as entrepreneurs. Cagetti and De Nardi (2006) define entrepreneurs as those self-employed business owners that have an active management in the firm. Salgado (2020) thus refer to four classifications of entrepreneurs that encompass the different alternatives considered in the literature. In this paper, we follow the definitions used in Quadrini (2000) and define entrepreneurs as self-employed household heads who are business owners in order to maximize the number of panel observations in PSID.[24]

Worker: a household head is considered to be worker if (1) her employment status is "Working now" or "Only temporarily laid off, sick leave or maternity leave", (2) she is neither self-employed nor a business owner, (3) her labor income is positive, and (4) her annual hours is greater than 260.

Retirement: a household head is considered to be retired if (1) her employment status is "Retired", and (2) her social security income is positive. Note that adding condition (2) is to avoid the misreport of retirement status. If we only rely on condition (1) to define retirement, we will see a pattern that around 5% of retirees in our sample are within the age group of 21-50.

Here is the detailed procedure about constructing variables household earnings and hourly wages:

1. Obtain the SRC sample that includes data for labor income, business income, employment status, gender, age, education, race, wealth, indicator on business owner for heads and wives of households.

2. Drop any observation (household) with missing age for either head or spouse.

3. Drop any observation with missing earnings but positive annual hours of work.

4. Drop any observation with positive earnings but zero annual hours of work.

5. Drop any observation with either head or spouse has nominal wage below half of the minimum wage.

6. Drop any household if neither the head nor the spouse is of working age, which we define as between the ages of 21 and 65.

[24] The head of the family unit (FU) in PSID must be at least 16 years old, and the person with the most financial responsibility in the FU. If this person is female and she has a husband in the FU, then he is designated as head.

A.2.1 Earnings and wealth from PSID

In this section, we plot the earnings and wealth over the life-cycle as well as the earnings distributions for different groups of people. We consider three groups: (1) entrants, which means first-year entrepreneurs, (2) incumbents which means entrepreneurs excluding entrants, and (3) workers. Earnings is defined as above. That is, workers' earnings are their labor income. Entrepreneurs' earnings are their labor income plus business income. The measure of wealth is the variable WEALTH2 as found in specific waves of PSID. This variable is constructed as sum of values of several asset types (family farm business, family accounts, assets, stocks, houses, and other real estate etc.) net of debt value.

In Figure A4(a), we plot the median earnings for entrants, incumbents, and workers over the life-cycle respectively, with the median earnings of workers with age 26-30 normalized to one. We can see that the median earnings of entrant entrepreneurs is always smaller than that of workers over the life-cycle. This may suggest non-pecuniary value of entry, which is consistent with the two elements—learning and Love of Business characteristics—in our model.[25]

In Figure A4(b), we plot the median wealth for entrants, incumbents, and workers over the life-cycle respectively, with the median wealth of workers with age 26-30 normalized to one. It is not surprising to see that entrepreneurs have higher median wealth level compared to workers, which is consistent with the stylized facts that entrepreneurs in general are relatively wealthier people. For example, in SCF, even though households headed by entrepreneurs make up only 7 to 8 percent of the population, they own nearly one-third of the wealth in the United States.

In Figure A5, we plot the distributions of earnings for entrants, incumbents, and workers respectively. We can see that both the earnings distributions of entrants and incumbents are more dispersed than that of workers, with the median of entrants' earnings smaller. While median earnings in entrepreneurs are lower than median wage earnings, a subset of entrepreneurs have very high earnings. This may suggest a learning story, as in, for instance, Dillon and Stanton (2018); Hincapié (2020), workers seeking to maximize expected lifetime earnings may rationally enter entrepreneurship to learn about their entrepreneurial ability, with the option to exit entrepreneurship as uncertainty resolves, even though their realized earnings during entrepreneurship are often low.

[25] We also admit that this pattern may be due to some mechanical reasons. For example, if a person enters entrepreneurship in October and is considered as an entrant entrepreneur in that year, then her earnings equals ten months' worker income and two months' entrepreneurial income. However, due to the limitations of PSID, we cannot rule out this kind of possibility.

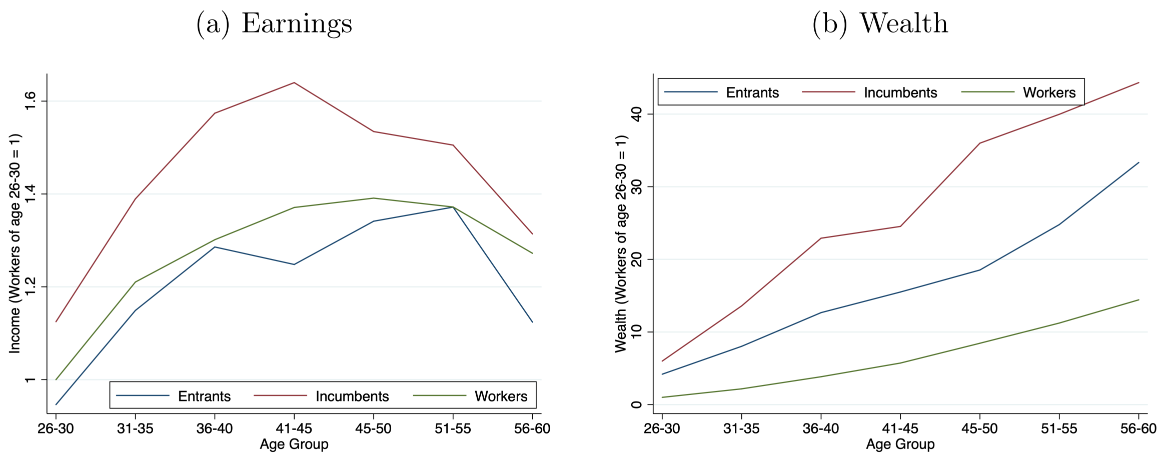

Figure A4: Median earnings and wealth over the life cycle

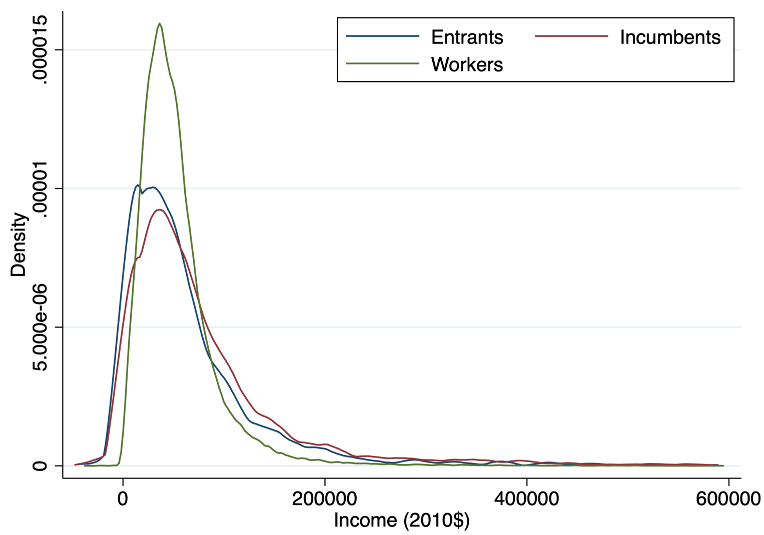

Figure A5: Earnings distribution (PSID)

A.2.2 Life-cycle patterns of entrepreneurship from CPS

In order to verify the robustness of the life-cycle patterns of entrepreneurship, we consider the Current Population Survey (CPS) that covers a much larger number of households compared to PSID. We construct a panel using monthly CPS data following the method developed by Drew, Flood, and Warren (2014). From the raw data, we extract a sample of heads of households from 1976 to 1997 at a monthly basis. All monetary variables (income and wealth) are deflated using the Personal Consumption Expenditure index (PCE) and expressed in 2010 dollars. The baseline sample considers households whose head is between 21 and 65 years old, both ends included. We report summary statistics of the sample in Table A6.

Table A6: Summary statistics (CPS sample)

	Wage Workers	Entrepreneurs	Labor Force	Total
Obs. per month	32,018	4,777	36,137	42,504
Age (mean)	40.1	44.4	40.5	41.9
Men (%)	75.0	89.9	77.1	73.3
College or above (%)	25.2	29.2	26.0	23.7

Note: The table reports statistics of a sample of heads of households between 21 and 65 years old. Each statistic is the sample average across all the survey waves between 1976 and 1997 at a monthly basis. Entrepreneurs are defined as self-employed heads of households. All monetary values are deflated by the PCE index and expressed in 2010 US dollars.

The entry and exit rate can thus only be computed at monthly frequency. We try to make our CPS sample as close to our benchmark PSID sample as possible. The CPS sample covers a similar periods (1975 - 1997) and the entrepreneurs in CPS are defined as self-employed household heads.[26] The age-profiles of entry, exit, and entrepreneurs share using CPS are reported in Figure A6. Although the numbers are not directly comparable between figures using the two datasets due to different definitions of entrepreneurs and different data frequencies, their life-cycle patterns are extremely similar to each other.

Figure A6: Entrepreneurship over the Life Cycle (CPS)

A.3 SCF

We consider two kinds of definitions of business income in SCF and check the share of negative or non-positive business income over the life cycle. The results are reported in Figure A7. In Definition 1, business income = schedule-C business income + taxable interest income + dividend income + capital gains + schedule-E business income + net operating loss. In Definition 2, business income = schedule-C business income + schedule-E business income.

[26]There is no variable on whether an individual is a business owner or not in CPS.

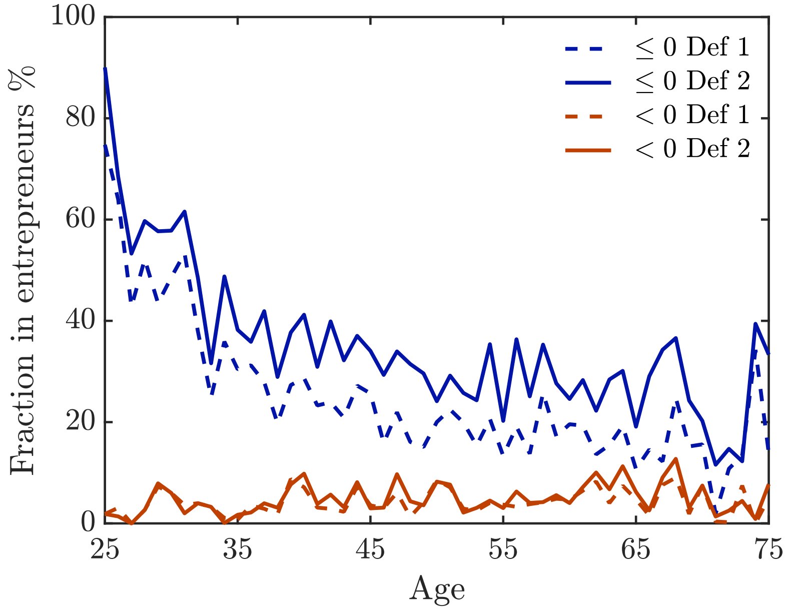

Figure A7: Non-positive business incomes in SCF

We also document age profiles of the entrepreneur share, earnings, and wealth in SCF, as in Figure A8. The aggregate entrepreneur share over the life cycle is consistent with the patterns in PSID and CPS where we use the same definition of entrepreneurs as the PSID.

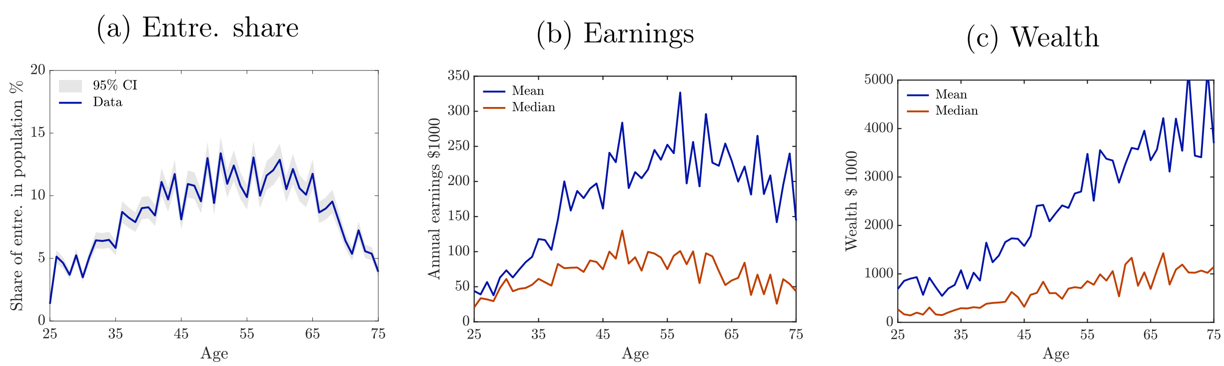

Figure A8: Age profile of entrepreneurial share, incomes, and assets in SCF

Finally, we compare several key statistics across PSID, SCF, and PSED as in Table A7. Notes: In IRS integrated business data, share of unincorporated is around 79% in 1996. Among all corporations, around 50% are s-corps.

Table A7: Comparison of entrepreneurs sample across PSID, SCF, and PSED

	PSID (96-04)	SCF (97-03)	PSED (98-04)
Frac. of Entrep. who have wage income	60%	77%	66%
Frac. of Entrep. whose businc>0.5*total inc	49%	56%	-
Share of unincorporated	67%	75%	>70%
Exit rate after 1 year operation	29%	-	30%

B Model

B.1 Definition of equilibrium

An individual with age j is indexed by states $\mathbf{x}_j = (x_e,\ a_j,\ \epsilon_{w,j},\ \tilde{\mu}_{e,j},\ \tilde{\nu}_{e,j},\ \epsilon_{e,j})$. Given a tax structure $\left\{\tau_c, T^{\omega}(\cdot), T^{b}(\cdot), \tau_{ss}\right\}$ and an initial distributions of workers and entrepreneurs over individual states $\left\{\Gamma_0^W(\mathbf{x}_0), \Gamma_0^E(\mathbf{x}_0)\right\}$, a **stationary recursive competitive equilibrium** comprises

- prices $\{w, r\}$ and social security benefits z
- a sequence of workers' policy functions on saving, occupation choice, consumption, and hours,
  $\left\{a_W^{'}(\mathbf{x}_j), o_W^{'}(\mathbf{x}_j), c_W^{'}(\mathbf{x}_j), h(\mathbf{x}_j)\right\}_{j=1}^{J^R-1}$, with associated value functions $\left\{V_j^W\right\}_{j=1}^{J^R-1}$, a sequence of entrepreneurs' policy functions on saving, occupation choice, consumption, capital rental, and labor hired, $\left\{a_E^{'}(\mathbf{x}_j), o_E^{'}(\mathbf{x}_j), c_E^{'}(\mathbf{x}_j), k(\mathbf{x}_j), n(\mathbf{x}_j)\right\}_{j=1}^{J^R-1}$, with associated value functions $\left\{V_j^E\right\}_{j=1}^{J^R-1}$, and individuals' policy functions after retirement on saving and consumption, $\left\{a_R^{'}(\mathbf{x}_j), c_R^{'}(\mathbf{x}_j)\right\}_{j=J^R}^{J}$, with associated value functions $\left\{V_j^R\right\}_{j=J^R}^{J}$
- factors demand of the corporate sector, $\{K_C, N_C\}$
- a sequence of distributions over idiosyncratic states for both workers and entrepreneurs $\left\{\Gamma_j^W(\mathbf{x}_j), \Gamma_j^E(\mathbf{x}_j)\right\}_{j=1}^{J}$

such that

1. Given prices w, r, the tax structure $\left\{\tau_c, T^{\omega}(\cdot), T^{b}(\cdot), \tau_{ss}\right\}$, and social security benefits z, the policy functions solve individual's problems (P1) and (P2).
2. The factors demand of the corporate sector solve equation (9).
3. Capital market clears:

$$\sum_{j=1}^{J} \int a^W(\mathbf{x}_j) d\Gamma_j^W(\mathbf{x}_j) + \sum_{j=1}^{J} \int a^E(\mathbf{x}_j) d\Gamma_j^E(\mathbf{x}_j) = K_C + \sum_{j=1}^{J^R-1} \int k(\mathbf{x}_j) d\Gamma_j^E(\mathbf{x}_j) \quad \text{(A1)}$$

4. Labor market clears:

$$\sum_{j=1}^{J^R-1} \int \epsilon_{\omega,j} \theta_j h_j(\mathbf{x}_j) \mathbb{I}_{\{h_j>0\}} d\Gamma_j^W(\mathbf{x}_j) = N_C + \sum_{j=1}^{J^R-1} \int n(\mathbf{x}_j) d\Gamma_j^E(\mathbf{x}_j) \quad \text{(A2)}$$

5. The Social Security system clears:

$$\tau_{ss}\left(\sum_{j=1}^{J^R-1}\int y_j^{\omega}(\mathbf{x}_j)d\Gamma_j^W(\mathbf{x}_j)+\sum_{j=1}^{J^R-1}\int y_j^{b}(\mathbf{x}_j)d\Gamma_j^E(\mathbf{x}_j)\right)=\sum_{j=J^R}^{J} z \tag{A3}$$

6. The government balances its budget:

$$G=\tau_c C+\sum_{j=1}^{J^R-1}\int T^{\omega}\left(y_j^{\omega}(\mathbf{x}_j)\right)d\Gamma_j^W(\mathbf{x}_j)+\sum_{j=1}^{J^R-1}\int T^{b}\left(y_j^{b}(\mathbf{x}_j)\right)d\Gamma_j^E(\mathbf{x}_j) \tag{A4}$$

7. The distributions of workers and entrepreneurs at the beginning of period j respectively, $\left\{\Gamma_j^W\left(\mathbf{x}_j\right),\Gamma_j^E\left(\mathbf{x}_j\right)\right\}_{j=1}^{J}$, evolve based on the individuals' policy functions and the autoregressive process for the exogenous productivity states.

B.2 Properties of the bequest function

Consider the problem of the last period of the life cycle, after which individuals die with probability 1:

$$\begin{aligned}&\max_{c,\ b} && u(c)+\mathcal{V}(b)\\ &s.t. && c+b=y\end{aligned}$$

F.O.C. (assuming an interior solution) gives:

$$\begin{aligned}&u'(c)=\mathcal{V}'(b)\quad \text{i.e.}\quad c^{-\tilde{\zeta}}=(\frac{\phi_b}{1-\phi_b})^{\tilde{\zeta}}(\frac{\phi_b}{1-\phi_b}c_b+b)^{-\tilde{\zeta}}\\ &\rightarrow c=c_b+(\frac{\phi_b}{1-\phi_b})^{-1}b\end{aligned}$$

Thus, the optimal choice of bequest $b^\star$

$$b^\star=\begin{cases}0 & \text{if } \ y\leq c_b\\ \phi_b(y-c_b) & \text{if } \ y>c_b\end{cases}$$

Thus, it is straightforward to see that the parameter $\phi_b\in[0,1)$ is the marginal propensity to bequeath and the parameter $c_b>0$ is the threshold consumption level below which people do not leave bequests.

B.3 More on model fit

First time entry In Figure A9, we plot the first time entrepreneurs as a share of total population which contains overlapping information with the figure on the entry rate over the life cycle. In addition, we compare the moments implied by the benchmark model with the case of perfect information.

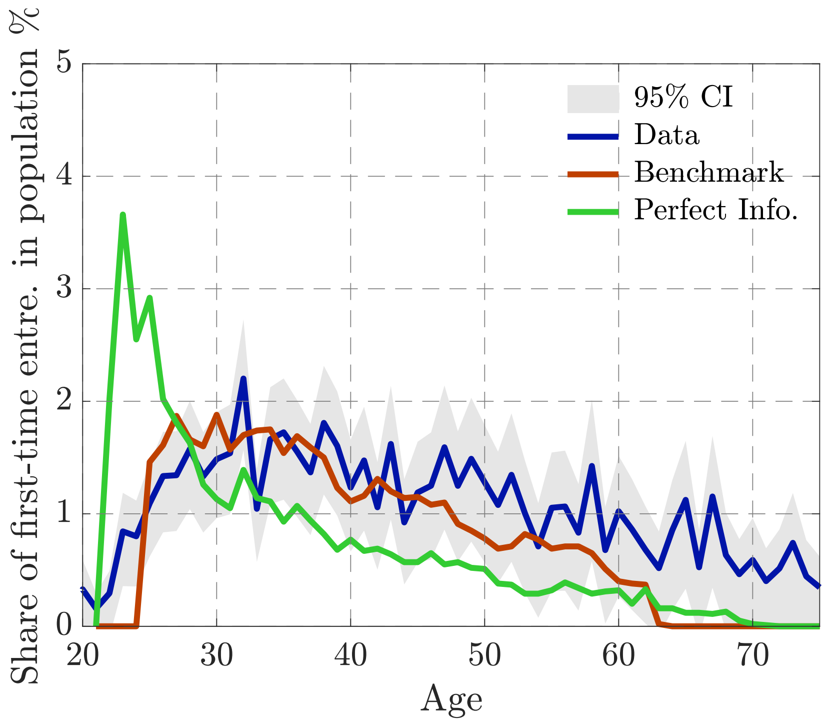

Figure A9: Model fit – First time entrepreneurs as a share of total population

Aggregate moments We further check if the moments on the macroeconomic level generated from our model is consistent with the data. The results are reported in Table A8.

Firm distribution in entrepreneurial sector We finally check the model fitness in distribution of firm size in terms of employment in the entrepreneurial sector. The statistics are reported in Table A9. We can see that our model is able to reproduce similar patterns to the empirical results we obtain from the Survey of Consumer Finance (SCF).

Exit of entrepreneurs around retirement For the increase in the exit rate after the age of 60, we do a decomposition of the exit rate to distinguish between the exit due to retirement and the exit due to switching occupation. The results are presented in Figure A10. Starting from the age of 62, increasing exit rate is only driven by the increasing retirement of people.

Table A8: Aggregate moments

	Values
Taxes to GDP ratios, %	
Total taxes	23.9
Consumption tax	2.4
Wage income tax	16.6
Business income tax	1.6
Assets/sales to GDP ratios, %	
Corporate fixed asset	261.6
Entrepreneurial fixed assets	48.3
Entrepreneurial sales	21.3

Table A9: Model fit – firm size distribution of entrepreneurs

	Data	Model
Share of entre. in population %	8.8	8.4
Share of hiring entre. %	66.1	82.9
Firm size distribution %		
1-5 Employees	69.2	42.3
6-10 Employees	11.9	40.2
11-20 Employees	6.5	17.5
>20 Employees	12.5	0.0

Our model well replicates the exit of entrepreneurs around the retirement. The key element that helps to match the data is voluntary retirement and bequest.

Wealth percentiles As shown in Figure A11 using the Survey of Consumer Finance, there is still high level of wealth accumulation at the later stage of individuals' life cycle. By incorporating the element of bequest into our model, the wealth percentiles over the life cycle for all the individuals and for entrepreneurs only are close to its empirical counterpart. Panel (a) is the data and panel (b) is generated from the model. Our model can replicate the overall life cycle pattern of asset accumulation. To be more specific, in both the data and our model, for the overall population, asset peaks for the age group of 60-64 and drops afterwards. Our model slightly overpredicts the drop in asset for the entrepreneurs at older ages. Our model does a good job in matching the wealth distribution for both the overall

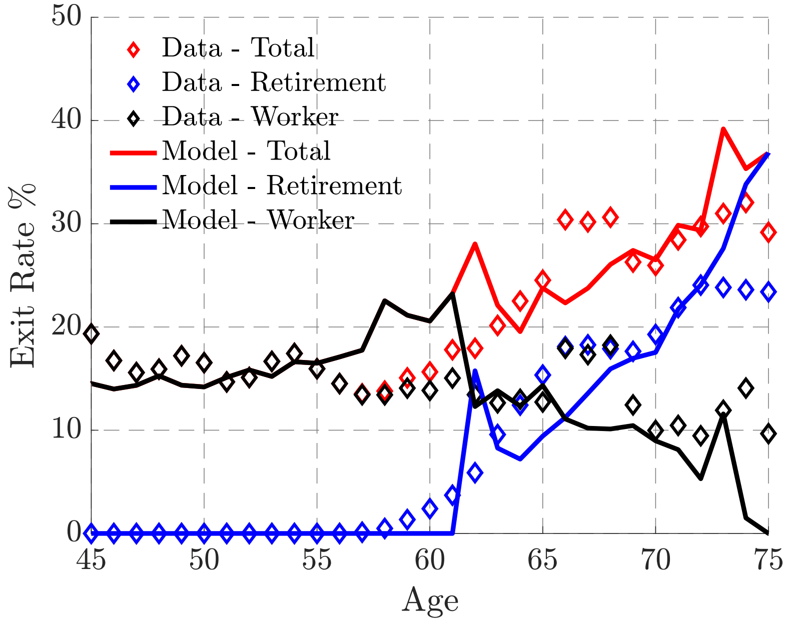

Figure A10: Model fit – exit of entrepreneurs around retirement

population and the entrepreneurs. Our model slightly underestimates the gaps between 95% percentile and the median.

Dispersion of LoB characteristic Results are shown in Table A10.

	All	Workers		Entrepreneurs	
		Data	Model	Data	Model
Mean	0.531	0.521	0.524	0.614	0.612
Std. Dev.	0.190	0.193	0.189	0.123	0.171

Table A10: Love of business characteristic by entrepreneur status

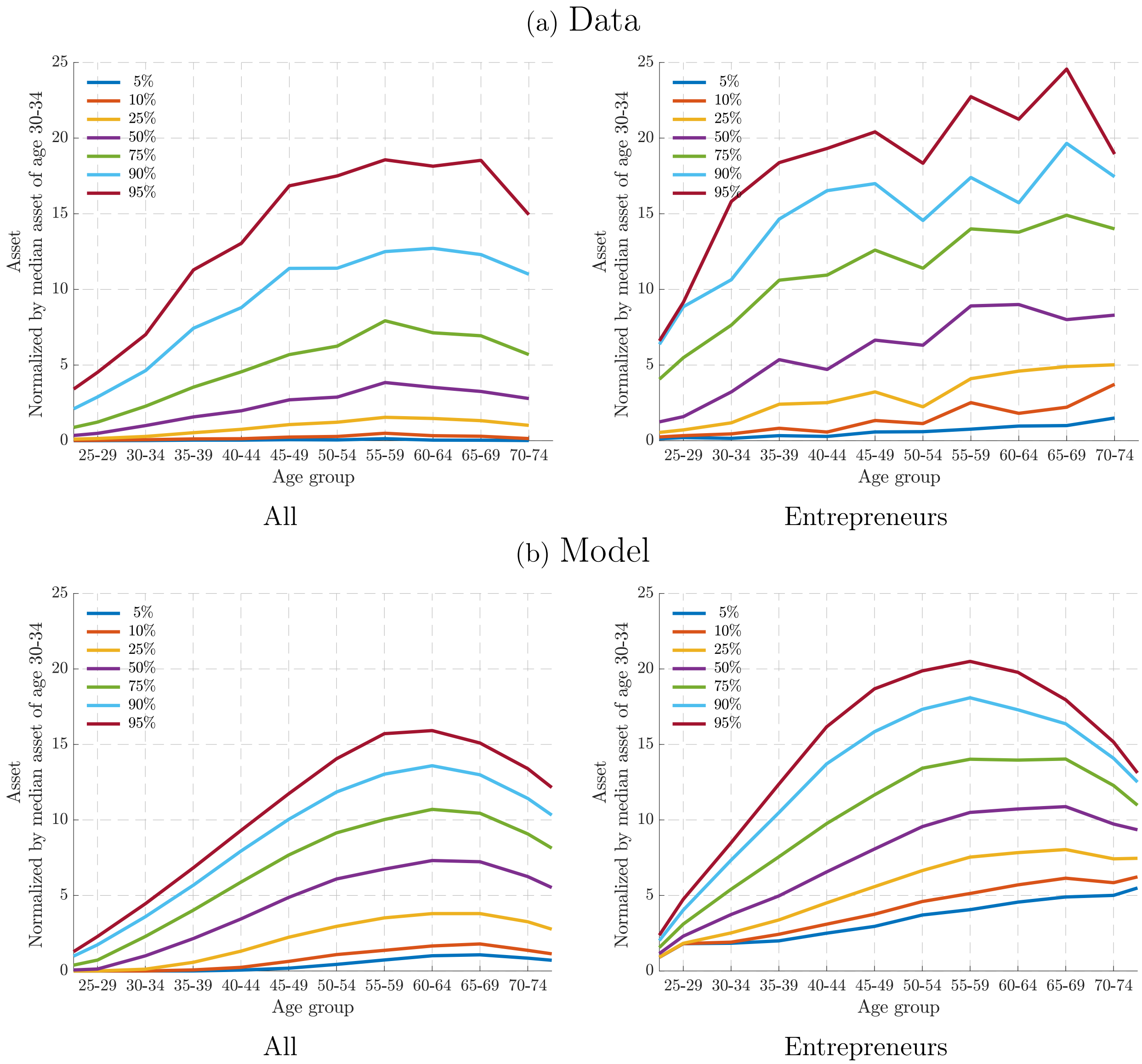

Figure A11: Model fit – asset percentiles over the life cycle

B.4 More on model implications

B.5 More on policy results

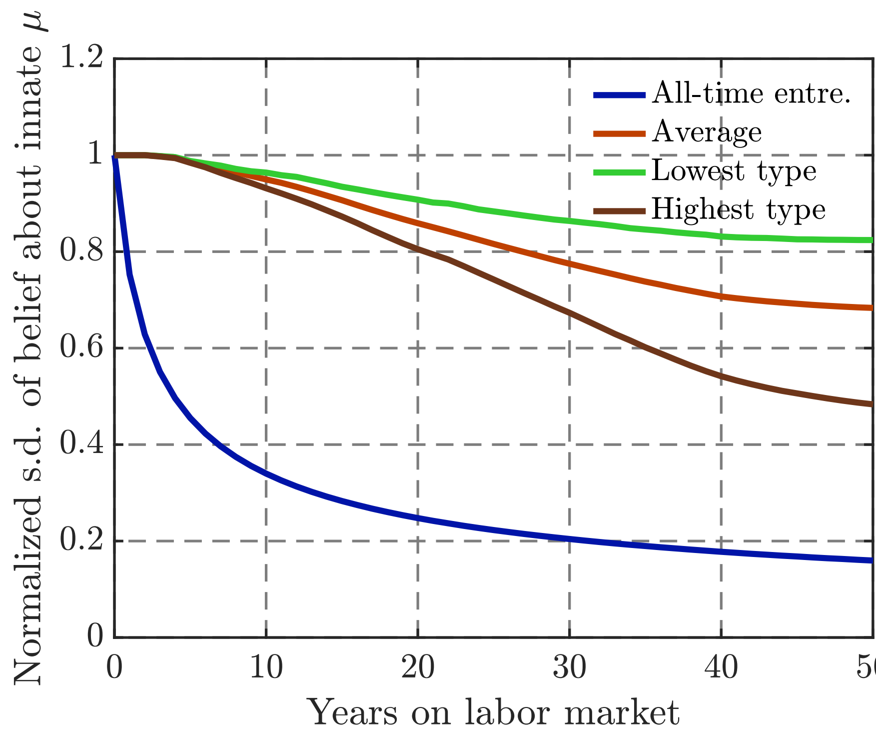

Figure A12: Bayesian Learning speed implied by the benchmark model

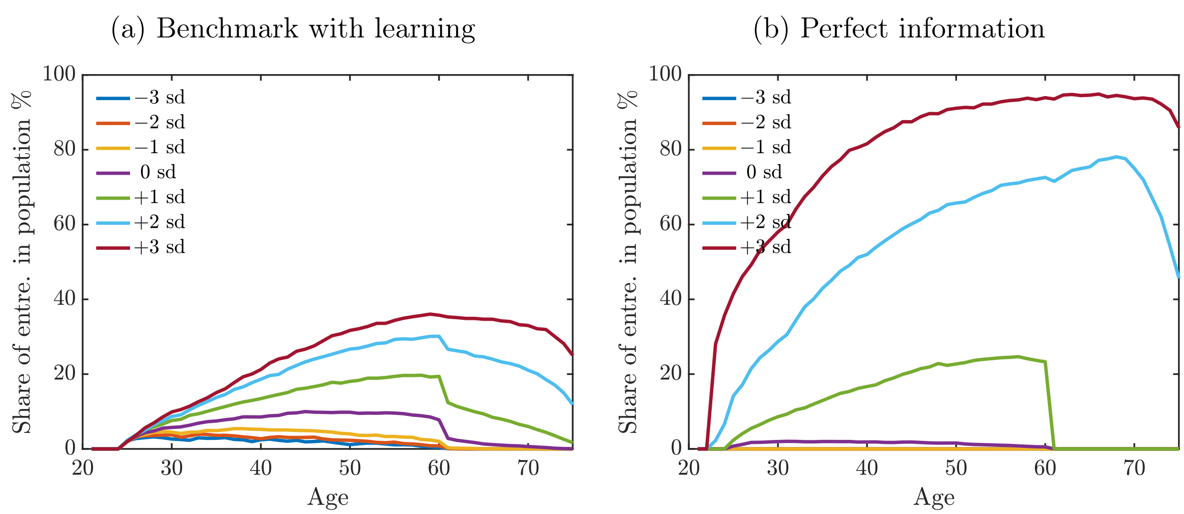

Figure A13: Lifecycle entrepreneur share by innate types

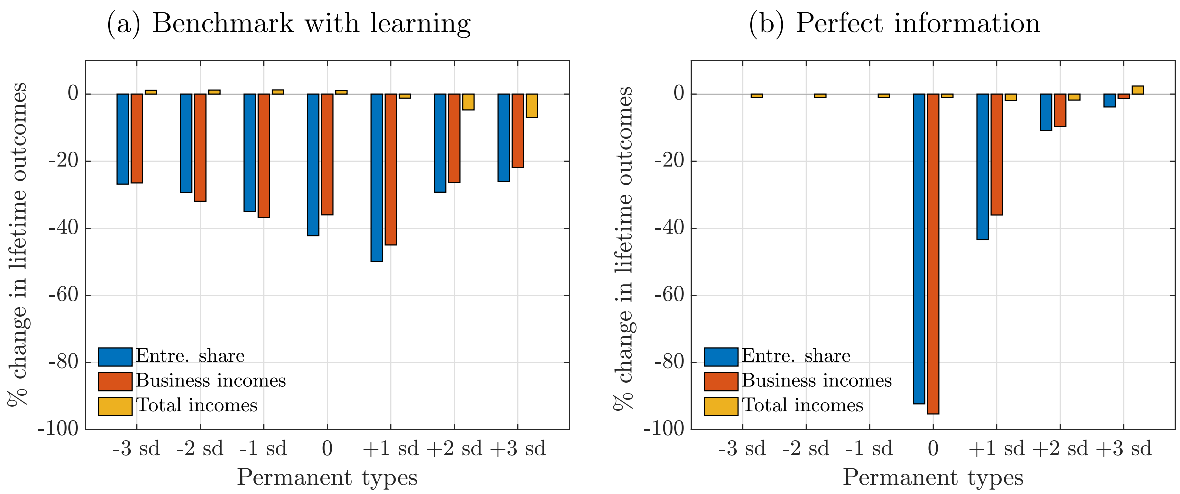

Figure A14: Change in lifetime outcomes by innate ability type

Table A11: Impacts of the revenue-neutral flat tax reform on aggregate moments

	With learning	Perfect information
Self-employment rate	–36.3%	–16.3%
Interest rate	4.7%	-5.0%
Wage rate	–1.1%	0.9%
Total output	–1.6%	1.8%
Private business	–26.5%	-1.4%
Coporate	16.5%	10.4%
Ave. private business output	16.1%	18.1%
Agg. employee hours	1.0%	1.3%
Agg. capital	5.5%	10.3%
AMTR-worker	1.4%	0.9%
AMTR-entre.	–46.3%	–45.6%
ATR-worker	0.8%	1.0%
ATR-entre.	-15.1%	–12.7%