Online Appendix to "Entrepreneurial Human Capital and Firm Dynamics"

A Additional Variable Definitions

Firm outcomes The paper examines the relationship between entrepreneur schooling and several firm outcomes. I use *sales* and *value added* as reported in SCIE. In section B.1 below I also use sales data as reported in QP, which extends further back in time than SCIE but is often reported for the year prior to the survey year, which might lead to survivor bias. *Employment* in figure F.2b is defined as the number of workers reported in QP, including both entrepreneurs and non-entrepreneurs, regardless of employment status and including unpaid workers. Section III.D in the paper uses several additional outcomes constructed from ISCO occupations as reported in QP and from SCIE financial statements data. These are defined as they are introduced in the analysis.

Controls *Sectors* are five-digit industries as reported in SCIE, which uses Eurostat's NACE Rev. 2 classification, *year* represents calendar years and *firm age* is calculated from the firm's reported year of incorporation in QP. SCIE also provides an indicator for firm births. When this indicator implies the firm is older than reported in QP, I use it instead of QP to define the year of incorporation. *Entrepreneur experience* represents the average potential experience of the firm's entrepreneurs. It is measured as entrepreneur age, reported in QP, minus years of schooling, minus six. *Non-entrepreneur schooling and experience* are the average years of schooling and experience for the workers that the firm employed at entry, and are both calculated in the same way as for entrepreneurs. *Earnings* in sections III.B and III.C in the paper are the sum of base salary and regular supplements divided by the number of hours worked, all reported in QP.

B Life Cycle Dynamics: Additional Results

B.1 Other Samples

To offer a fuller picture of the life cycle than the 2004-2007 cohorts used in the paper, figure F.3a plots coefficients for the 1995 to 1997 cohorts, using sales data from QP. These are the three oldest cohorts I can observe from entry, and I can track them up to age 20. The patterns are the same as for the 2004-2007 cohorts up to age 10, except that size differences at entry are somewhat larger. Firms in the top group are twice as large at entry than those in the bottom group, which corresponds roughly to size differences at age one in figure 1 in the paper. This could be driven by survivor bias in the QP sales data, which are often reported with a one-year lag as explained above. By age 10, firms in the top group are 2.5 times larger, nearly the same as in figure 1, and by age 20 they are 2.6 times larger, again suggesting growth paths are mostly parallel at older ages.

This is as far as one can go tracking cohorts observed from entry in the data. Figure F.3b offers suggestive evidence on firm dynamics beyond age 20 by plotting schooling-by-age coefficients estimated in the cross-section of firms in 2017. To include older firms, I proxy for entrepreneur schooling with the education of the *first* top managers that the firm reports in the data, not necessarily at entry. The implicit assumption is that top manager schooling is a persistent firm characteristic. Figure F.4 shows that this is indeed the case by plotting the average years of schooling of top managers over the life cycle for firms in the 1995-1997 cohorts. More broadly, the one-year autocorrelation of top manager schooling in the full sample is 0.95 and the ten-year autocorrelation is 0.79.

The cross-sectional patterns are consistent with the cohort evidence up to age 20, and firms continue on similar growth paths at least up to age 40. Beyond age 40, differences across groups appear to widen again, although at older ages the proxy for entrepreneur schooling becomes less defensible, and it is harder to rule out an increased role for assortative matching between firms and managers.

B.2 Stability Over Time

Figure F.5 shows that the linear relationship documented in figure 4 in the paper is stable over time. To construct this figure, I add interactions with cohort dummies to the schooling-by-age terms in equation (2) in the paper, and estimate the resulting equation for all firms in the 2004 to 2012 cohorts, including sector-by-year fixed effects to account for differences in sector composition across cohorts.[1] Since I only observe the 2012 cohort up to age 5, I restrict the regression to firms aged 5 or less. I then plot the schooling coefficients at ages 1, 2 and 5 for each cohort. The coefficients are relatively similar across cohorts, ranging between 0.037 and 0.044 at age one and between 0.061 and 0.076 at age five, and do not seem to exhibit a trend over time. It should be noted that during the corresponding sample period, from 2004 to 2017, average years of schooling in the working population rose by over 2 years in the QP data, from 8.17 to 10.42. In addition, Portugal experienced a financial crisis and a deep recession from 2011 to 2013, during which access to external finance for firms is likely to have been severely restricted. This lends some support to the externality

[1] Note I cannot additionally interact the firm age dummies with cohort dummies, since these interactions would be collinear with year fixed effects.

validity of the estimated coefficients.

B.3 Other Specifications

Table E.2 presents additional robustness checks by estimating several versions of equation (2) in the paper using the 2004-2007 cohorts sample. The table reports results for sales, but the results are very similar for value added. Column one reports baseline estimates. Column two removes controls for non-entrepreneur schooling and experience, which could be considered a mechanism, rather than held constant. The entrepreneur schooling-by-age coefficients are similar to the baseline estimates, suggesting that assortative matching between entrepreneurial and non-entrepreneurial human capital does not play much of a role in driving firm dynamics.

About three quarters of the firms in the sample have only one entrepreneur according to my definition, while the remaining ones have two or more. Column three controls for the log of the number of entrepreneurs and again the results are very similar. In column four, I define a unique entrepreneur for each firm by taking the individual with the highest wage among those identified as entrepreneurs. When there are ties in wages, I take the oldest individual, and then drop a residual number of observations where age does not break the tie. The correlation between entrepreneur schooling measured in this way and my baseline measure is 0.98, and the results are again very similar. Finally, columns five and six cluster standard errors at the sector and year level, respectively, instead of at the firm level.

B.4 Measurement Error in Expected Earnings

The presence of ν in the error term in equation (6) in the paper attenuates the coefficient on $\ln w$. This amplifies the coefficient on s if schooling and ability are positively correlated, but also attenuates the bias correction. If ν represents measurement error uncorrelated with s, the net effect on the bias-corrected estimate of β^e depends on the interaction of measurement error and ability bias in a regression of labor market earnings on the entrepreneur's schooling.

Formally, the probability limits of the coefficients on $\ln w$ and s equal $\frac{\lambda^e}{\lambda^w}\frac{\sigma_e^2}{\sigma_e^2+\sigma_\nu^2}$ and $\beta^e - \frac{\lambda^e}{\lambda^w}\beta^w + \beta^{w^*}\frac{\lambda^e}{\lambda^w}\left(1-\frac{\sigma_e^2}{\sigma_e^2+\sigma_\nu^2}\right)$ respectively, where σ_ν^2 is the variance of ν, σ_e^2 is the variance of the residual from a regression of $E(\ln w)$ on s and X, and β^{w^*} is the coefficient on s in that regression. β^{w^*} in turn equals $\beta^w + \lambda^w\zeta$, where ζ is the coefficient on s from a regression of b on s and X. Applying the bias correction to the coefficient on s therefore leads to a consistent estimate of

$$\beta^e - \frac{\lambda^e}{\lambda^w}\beta^w + (\beta^w + \lambda^w\zeta)\frac{\lambda^e}{\lambda^w}\left(1-\frac{\sigma_e^2}{\sigma_e^2+\sigma_\nu^2}\right) + \beta^w\frac{\lambda^e}{\lambda^w}\frac{\sigma_e^2}{\sigma_e^2+\sigma_\nu^2} = \beta^e + \lambda^w\zeta\frac{\lambda^e}{\lambda^w}\left(1-\frac{\sigma_e^2}{\sigma_e^2+\sigma_\nu^2}\right)$$

The literature on returns to schooling has found the ability bias term $\lambda^w\zeta$ to be small, on the order of 10 percent of β^w (Card, 1999), which implies that the bias term on the right-hand side will be minimal even if measurement error in the outside option is severe. For example, suppose that measurement error is such that $\frac{\sigma_e^2}{\sigma_e^2+\sigma_\nu^2} = 0.5$, which implies that the coefficient on $\ln w$ is attenuated by 50 percent. Assuming a return to schooling of $\beta^w = 8\%$ and using the coefficient on $\ln w$ at age 10 from column two in table 1 in the paper, the bias on β_{10}^e would equal $0.08 \times 0.1 \times 0.6474 = 0.0052$. This compares with an estimate for β_{10}^e of 0.0778 in column two of the same table.

B.5 Sector Heterogeneity

Figure F.6 presents additional evidence on sector heterogeneity along five different dimensions: human capital intensity (Ciccone and Papaioannou, 2009), external finance dependence (Rajan and Zingales, 1998), contract intensity (Nunn, 2007), physical capital intensity, and finally social networks intensity (Fracassi, 2017). For each dimension, the figure plots schooling-by-age coefficients from estimating equation (2) in the paper separately for above and below median sectors.

Data on external financial dependence is from Kroszner, Laeven and Klingebiel (2007), who reconstruct the Rajan and Zingales (1998) measure at the 3-digit ISIC level. Data on physical capital intensity is from Bartelsman and Gray (1996), as reported in Ciccone and Papaioannou (2009). Except for social network intensity, these classifications only cover the manufacturing sector. Fracassi (2017) only reports the top 10 and bottom 10 sectors by social network intensity, so I use this instead of above and below median sectors. In each case, I manually match industries to the NACE rev 2 codes used in SCIE.

The coefficients are larger in more human capital intense sectors, in sectors more dependent on external finance, in more contract intense sectors, in less physical capital intense sectors and in more social network intense sectors. However, the differences are smaller than those between high-tech and other sectors shown in figure 9 in the paper, and mostly insignificant.

Figures F.7 and F.8 present sector specific estimates of equation (2) in the paper at the one and two digit levels.

C Model Derivations

Throughout the derivations I use the following result on integrals of normal distributions (Owen, 1980):

$$\int_{-\infty}^{\infty} \Phi(a+bx)\phi(x)dx = \Phi\left(\frac{a}{\sqrt{1+b^2}}\right) \tag{1}$$

where ϕ and Φ denote the density and CDF of the standard normal distribution.

C.1 Productivity Growth

Let z_g denote cumulative growth in z. To derive its stationary distribution, consider first the case of agents in the growth phase. Following the analogous derivation in Jones and Kim (2018), an agent who remains in the growth phase at age x has $z_g(x) = x(\mu_0 + \mu_1 s)$, from equation (9) in the paper. This implies that the density of agents with growth $z_g(x)$ is given by the density of those with age $x(z_g) = \frac{z_g}{\mu_0+\mu_1 s}$. Given exit and transition to maturity at rates δ and m, the stationary age distribution of agents in the growth phase will be exponential with parameter $\delta + m$. The density of growth for these agents will therefore be given by

$$f^g(z_g; \alpha_s) = \alpha_s e^{-\alpha_s z_g} \tag{2}$$

where α_s is given by equation (15) in the paper.

Now consider the distribution for agents in the mature state. Since productivity in the mature state is constant, the evolution of the corresponding density $f^m(z_g; s)$ only depends on the fraction of agents who transition from the growth state and on exit:

$$\frac{\partial f^m(z_g, t; \alpha_s)}{\partial t} = m f^g(z_g, t; \alpha_s) - \delta f^m(z_g, t; \alpha_s)$$

In a stationary distribution, the density for agents in the mature phase must then satisfy

$$f^m(z_g; \alpha_s) = \frac{m}{\delta} f^g(z_g; \alpha_s)$$

This implies that agents in the mature phase inherit the distribution of those in the growth phase, and that the stationary distribution of z_g for all agents with schooling s will be given by (2).

C.2 Distribution of Firm Productivity

To derive equation (16) in the paper, note first that $f^*(z)$ is expressed in terms of $f(z)$ and $F(z)$, the PDF and CDF of z in the population. For an EMG distribution with mean vs, variance σ_η^2 and rate α_s, these functions are defined as follows:

$$f\left(z; vs, \sigma_\eta^2, \alpha_s\right) = \alpha_s e^{-\alpha_s (z - vs - \alpha_s \sigma_\eta^2/2)} \Phi\left(\frac{z - vs - \alpha_s \sigma_\eta^2}{\sigma_\eta}\right) \tag{3}$$

$$F\left(z; vs, \sigma_\eta^2, \alpha_s\right) = \Phi\left(\frac{z - vs}{\sigma_\eta}\right) - e^{-\alpha_s\left(z - vs - \alpha_s \frac{\sigma_\eta^2}{2}\right)} \Phi\left(\frac{z - vs - \alpha_s \sigma_\eta^2}{\sigma_\eta}\right) \tag{4}$$

$f^*(z)$ is given by multiplying $f(z)$ by the fraction of active entrepreneurs for each z, and dividing by the overall entrepreneurship rate. The fraction of active entrepreneurs for a given z is $\Phi\left(\frac{z-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)$. This follows from equation (13) in the paper and the assumptions on h, which imply that z^* is normally distributed with mean $z_0^*+\frac{\bar{r}}{\sigma-1}s$ and standard deviation $\sigma_h(s)/(\sigma-1)$.

To derive the entrepreneurship rate, integrate $f(z)\Phi\left(\frac{z-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)$ over all z:

$$\int_{-\infty}^{\infty}\alpha_s e^{-\alpha_s(z-vs-\alpha_s\sigma_\eta^2/2)}\Phi\left(\frac{z-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)\Phi\left(\frac{z-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz$$

Write this as a double integral:

$$\int_{-\infty}^{\infty}\int_{z^*}^{\infty}\alpha_s e^{-\alpha_s(z-vs-\alpha_s\sigma_\eta^2/2)}\Phi\left(\frac{z-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)dz\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^*$$

Use the definition of the EMG CDF in (4) to evaluate the inner integral:

$$\int_{-\infty}^{\infty}\left[\Phi\left(\frac{vs-z^*}{\sigma_\eta}\right)+e^{-\alpha_s\left(z^*-vs-\alpha_s\frac{\sigma_\eta^2}{2}\right)}\Phi\left(\frac{z^*-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)\right]\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^*$$

Use (1) to evaluate the first integral, and write the second one as a double integral:

$$\Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)$$
$$+\int_{-\infty}^{\infty}\int_{z}^{\infty}e^{-\alpha_s\left(z^*-vs-\alpha_s\frac{\sigma_\eta^2}{2}\right)}\frac{\sigma-1}{\sigma_h(s)\sigma_\eta}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^*\phi\left(\frac{z-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)dz$$

The inner integral in the second term is the partial expectation of a log-normal variable from z to ∞, leading to:

$$\Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)+e^{-\alpha_s\left(z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\frac{\sigma_\xi^2(s)}{2}\right)}$$
$$\times\int_{-\infty}^{\infty}\Phi\left(\frac{-z+z_0^*+\frac{\bar{r}}{\sigma-1}s-\alpha_s\left(\frac{\sigma_h(s)}{\sigma-1}\right)^2}{\sigma_h(s)/(\sigma-1)}\right)\frac{1}{\sigma_\eta}\phi\left(\frac{z-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)dz$$

The remaining integral can be evaluated using (1), yielding:

$$\Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)+e^{-\alpha_s\left(z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\frac{\sigma_\xi^2(s)}{2}\right)}\Phi\left(\frac{z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\sigma_\xi^2(s)}{\sigma_\xi(s)}\right) \tag{5}$$

Using the definition of the EMG CDF in (4), this can be written as $1-F\left(z_0^*;\left(v-\frac{\bar{r}}{\sigma-1}\right)s,\sigma_\xi^2(s),\alpha_s\right)$, which is the expression in the paper.

C.3 Expected Log Productivity at Entry

Start with agents who select into entrepreneurship at birth, and let Θ_{born} denote the fraction of agents who do so. This is given by

$$\begin{aligned}
\Theta_{born} &= \int_{-\infty}^{\infty}\int_{z^*}^{\infty}\frac{1}{\sigma_\eta}\phi\left(\frac{z-vs}{\sigma_\eta}\right)dz\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^* \\
&= \int_{-\infty}^{\infty}\Phi\left(\frac{vs-z^*}{\sigma_\eta}\right)\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^* \\
&= \Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)
\end{aligned}$$

where the last step uses (1). This corresponds to the first term of (5). Expected log productivity for these agents can then be expressed as

$$E_{born}(z|s,a=0)=\frac{\int_{-\infty}^{\infty}\int_{z^*}^{\infty}z\frac{1}{\sigma_\eta}\phi\left(\frac{z-vs}{\sigma_\eta}\right)dz\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^*}{\Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)}$$

The inner integral can be evaluated as the partial expectation of a normal variable, which gives

$$E_{born}(z|s,a=0)=\frac{\int_{-\infty}^{\infty}\left[vs\Phi\left(\frac{vs-z^*}{\sigma_\eta}\right)+\sigma_\eta\phi\left(\frac{z^*-vs}{\sigma_\eta}\right)\right]\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^*}{\Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)}$$

The first term can be evaluated using (1). The second can be solved to yield:

$$E_{born}(z|s,a=0) = \frac{vs\Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)+\frac{\sigma_\eta^2}{\sigma_\xi(s)}\phi\left(-\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)}{\Phi\left(\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)}$$

$$= vs + \frac{\sigma_\eta^2}{\sigma_\xi(s)}M\left(-\frac{\left(v-\frac{\bar{r}}{\sigma-1}\right)s-z_0^*}{\sigma_\xi(s)}\right)$$

where $M(x)=\frac{\phi(x)}{\Phi(-x)}$ is the inverse Mill's ratio. The first term is the mean of productivity at birth across all agents, while the second term reflects selection from the fact that only those agents born with $z \geq z^*$ start as entrepreneurs.

Next consider agents who transition into entrepreneurship after birth. These are agents born with $z < z^*$ but whose productivity grows to reach z^* at some point in their lives. The fraction of agents Θ_{switch} who meet this condition is given by

$$\Theta_{switch} = \int_{-\infty}^{\infty}\int_{-\infty}^{z^*} e^{-\alpha_s(z^*-z)}\frac{1}{\sigma_\eta}\phi\left(\frac{z-vs}{\sigma_\eta}\right)dz\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^*$$

The inner term is the partial expectation of a log-normal variable, which leads to

$$\Theta_{switch} = \int_{-\infty}^{\infty} e^{-\alpha_s(z^*-vs-\alpha_s\sigma_\eta^2/2)}\Phi\left(\frac{z^*-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right)dz^*$$

Completing the square involving z^* in the exponential term and in ϕ yields

$$\begin{aligned}\Theta_{switch} =& e^{-\alpha_s\left(z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\frac{\sigma_\xi^2(s)}{2}\right)}\\ &\times\int_{-\infty}^{\infty}\Phi\left(\frac{z^*-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s+\alpha_s\left(\frac{\sigma_h(s)}{\sigma-1}\right)^2}{\sigma_h(s)/(\sigma-1)}\right)dz^*\end{aligned}$$

Using (1) to evaluate the remaining integral gives the final expression, which corresponds to the second term of (5):

$$\Theta_{switch} = e^{-\alpha_s\left(z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\frac{\sigma_\xi^2(s)}{2}\right)}\Phi\left(\frac{z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\sigma_\xi^2(s)}{\sigma_\xi(s)}\right)$$

Noting that all agents who switch into entrepreneurship enter with productivity z^*, expected log productivity at entry for these agents is then given by

$$E_{switch}(z|s,a=0) = \frac{\int_{-\infty}^{\infty} z^* \int_{-\infty}^{z^*} e^{-\alpha_s(z^*-z)} \frac{1}{\sigma_\eta}\phi\left(\frac{z-vs}{\sigma_\eta}\right) dz \frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right) dz^*}{e^{-\alpha_s\left(z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\frac{\sigma_\xi^2(s)}{2}\right)}\Phi\left(\frac{z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\sigma_\xi^2(s)}{\sigma_\xi(s)}\right)}$$

$$= \frac{\int_{-\infty}^{\infty} z^*\Phi\left(\frac{z^*-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s+\alpha_s\left(\frac{\sigma_h(s)}{\sigma-1}\right)^2}{\sigma_h(s)/(\sigma-1)}\right) dz^*}{\Phi\left(\frac{z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\sigma_\xi^2(s)}{\sigma_\xi(s)}\right)}$$

where the second line uses the derivations for Θ_{switch} above. Writing the numerator as a double integral leads to an expression of the same form as the one for $E_{born}(z|s,a=0)$:

$$E_{switch}(z|s,a=0) = \frac{\int_{-\infty}^{\infty}\int_{z}^{\infty} z^*\frac{\sigma-1}{\sigma_h(s)}\phi\left(\frac{z^*-z_0^*-\frac{\bar{r}}{\sigma-1}s+\alpha_s\left(\frac{\sigma_h(s)}{\sigma-1}\right)^2}{\sigma_h(s)/(\sigma-1)}\right) dz^*\frac{1}{\sigma_\eta}\phi\left(\frac{z-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right) dz}{\Phi\left(\frac{z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\sigma_\xi^2(s)}{\sigma_\xi(s)}\right)}$$

Following the same steps as for $E_{born}(z|s,a=0)$ yields the final expression:

$$E_{switch}(z|s,a=0) = z_0^* + \frac{\bar{r}}{\sigma-1}s - \frac{\alpha_s\sigma_h^2(s)}{(\sigma-1)^2} + \frac{\sigma_h^2(s)}{(\sigma-1)^2\sigma_\xi(s)}M\left(-\frac{z_0^*+\left(\frac{\bar{r}}{\sigma-1}-v\right)s-\alpha_s\sigma_\xi^2(s)}{\sigma_\xi(s)}\right)$$

The first two terms correspond to the mean of z^*. The remaining terms represent selection effects. The third term is negative, and is driven by the fact that the higher z^* is, the less likely that an agent's productivity will grow to the point of transition into entrepreneurship. The fourth term is positive, and reflects the fact that only agents born with $z^* > z$ ever transition into entrepreneurship.

Finally, expected log productivity at entry across all agents is a weighted average of the two types:

$$E(z|s,a=0) = \frac{E_{born}(z|s,a=0)\Theta_{born} + E_{switch}(z|s,a=0)\Theta_{switch}}{\Theta_{born}+\Theta_{switch}}$$

C.4 TFP

The expression for TFP in equation (21) in the paper is a function of Z^*, H^* and H. I derive each in turn. Z^* can be expressed as:

$$Z^* = \sum_S \theta_s \int_{-\infty}^{\infty} \int_{z^*}^{\infty} e^{(\sigma-1)z} f(z) dz \frac{\sigma-1}{\sigma_h(s)} \phi\left(\frac{z^* - z_0^* - \frac{\bar{r}}{\sigma-1}s}{\sigma_h(s)/(\sigma-1)}\right) dz^*$$

where $f(z)$ is given by (3). The inner integral, with z^* fixed, is evaluated in Proposition 5 of Sager and Timoshenko (2019) for a double EMG distribution. Following the same approach yields

$$\begin{aligned}\int_{z^*}^{\infty} e^{(\sigma-1)z} f(z) dz = &\int_{z^*}^{\infty} e^{(\sigma-1)z} \frac{1}{\sigma_\eta} \phi\left(\frac{z - vs}{\sigma_\eta}\right) dz \int_0^{\infty} e^{(\sigma-1)z_g} \alpha_s e^{-\alpha_s z_g} dz_g \\ &+ \int_{-\infty}^{z^*} \int_{z^*-z}^{\infty} e^{(\sigma-1)z_g} \alpha_s e^{-\alpha_s z_g} dz_g e^{(\sigma-1)z} \frac{1}{\sigma_\eta} \phi\left(\frac{z - vs}{\sigma_\eta}\right) dz\end{aligned}$$

The first term corresponds to agents who select into entrepreneurship at birth, and the second to those who switch into entrepreneurship later in life. Evaluating these integrals gives

$$\begin{aligned}&\int_{z^*}^{\infty} e^{(\sigma-1)z} f(z) dz = e^{(\sigma-1)vs + \frac{(\sigma-1)^2\sigma_\eta^2}{2}} \frac{\alpha_s}{\alpha_s - \sigma + 1} \\ &\times \left[\Phi\left(\frac{vs + (\sigma-1)\sigma_\eta^2 - z^*}{\sigma_\eta}\right) + e^{-(\alpha_s - \sigma + 1)\left[z^* - vs - (\sigma-1)\sigma_\eta^2 - (\alpha_s - \sigma+1)\frac{\sigma_\eta^2}{2}\right]} \Phi\left(\frac{z^* - vs - \alpha_s \sigma_\eta^2}{\sigma_\eta}\right)\right]\end{aligned}$$

Plugging into the expression for Z^* leads to two integrals of the same form as those involved in the derivation of (5). Solving those leads to:

$$\begin{aligned}Z^* = &\sum_S \theta_s e^{(\sigma-1)vs + (\sigma-1)^2\frac{\sigma_\eta^2}{2}} \frac{\alpha_s}{\alpha_s - \sigma + 1} \left[\Phi\left(\frac{\left(v - \frac{\bar{r}}{\sigma-1}\right)s - z_0^* + (\sigma-1)\sigma_\eta^2}{\sigma_\xi(s)}\right)\right. \\ &+ e^{-(\alpha_s-\sigma+1)\left[z_0^* + \left(\frac{\bar{r}}{\sigma-1} - v\right)s - (\sigma-1)\sigma_\eta^2 - (\alpha_s - \sigma+1)\frac{\sigma_\xi^2(s)}{2}\right]} \\ &\left.\times \Phi\left(\frac{z_0^* + \left(\frac{\bar{r}}{\sigma-1} - v\right)s - (\sigma-1)\sigma_\eta^2 - (\alpha_s - \sigma + 1)\sigma_\xi^2(s)}{\sigma_\xi(s)}\right)\right]\end{aligned}$$

Using the definition of the EMG CDF in (4), the term in brackets can be rewritten to yield the expression for Z^* in the paper:

$$Z^* = \sum_S \theta_s e^{(\sigma-1)vs+(\sigma-1)^2\frac{\sigma_\eta^2}{2}} \frac{\alpha_s}{\alpha_s-\sigma+1}\left[1-F\left(z_0^*;\left(v-\frac{\bar{r}}{\sigma-1}\right)s+(\sigma-1)\sigma_\eta^2, \sigma_\xi^2(s), \alpha_s-\sigma+1\right)\right]$$

Using (4) and equation (17) in the paper, H^* can be expressed as

$$\begin{aligned}
H^* = &\sum_S \theta_s \int_{-\infty}^{\infty} e^h \frac{1}{\sigma_h(s)}\phi\left(\frac{h-\bar{r}s}{\sigma_h(s)}\right) \\
&\times\left[\Phi\left(\frac{z_0^*+\frac{h}{\sigma-1}-vs}{\sigma_\eta}\right) - e^{-\alpha_s\left(z_0^*+\frac{h}{\sigma-1}-vs-\alpha_s\frac{\sigma_\eta^2}{2}\right)}\Phi\left(\frac{z_0^*+\frac{h}{\sigma-1}-vs-\alpha_s\sigma_\eta^2}{\sigma_\eta}\right)\right] dh
\end{aligned}$$

This integral is of the same form as the ones in the expressions above, and solving it using a similar approach leads to:

$$\begin{aligned}
H^* = &\sum_S \theta_s e^{\bar{r}s+\frac{\sigma_h(s)^2}{2}}\left[\Phi\left(\frac{z_0^*-\left(v-\frac{\bar{r}}{\sigma-1}\right)s+\frac{\sigma_h^2(s)}{(\sigma-1)}}{\sigma_\xi(s)}\right)\right. \\
&\left.-e^{-\alpha_s\left(z_0^*-\left(v-\frac{\bar{r}}{\sigma-1}\right)s+\frac{\sigma_h^2(s)}{(\sigma-1)}-\alpha_s\frac{\sigma_\xi^2(s)}{2}\right)}\Phi\left(\frac{z_0^*-\left(v-\frac{\bar{r}}{\sigma-1}\right)s+\frac{\sigma_h^2(s)}{(\sigma-1)}-\alpha_s\sigma_\xi^2(s)}{\sigma_\xi(s)}\right)\right] \\
= &\sum_S \theta_s e^{\bar{r}s+\frac{\sigma_h(s)^2}{2}} F\left(z_0^*;\left(v-\frac{\bar{r}}{\sigma-1}\right)s-\frac{\sigma_h^2(s)}{(\sigma-1)}, \sigma_\xi^2(s), \alpha_s\right)
\end{aligned}$$

Lastly, H is simply given by

$$\begin{aligned}
H &= \sum_S \theta_s \int_{-\infty}^{\infty} e^h \frac{1}{\sigma_h(s)}\phi\left(\frac{h-\bar{r}s}{\sigma_h(s)}\right) dh \\
&= \sum_S \theta_s e^{\bar{r}s+\frac{\sigma_h(s)^2}{2}}
\end{aligned}$$

Plugging the expressions for Z^*, H^* and H into equation (20) in the paper yields the final expression for TFP.

D Estimation

The parameter m is estimated using the minimum distance procedure developed by Chamberlain (1984). First, let $\tilde{g}_{s,a}(m)$ denote expected firm growth from age one to age a for schooling level s. Using equations (18), (22) and (23) in the paper, this can be expressed as

$$\tilde{g}_{s,a}(m) = (\sigma - 1)\frac{\delta + m}{m}\frac{(s_i - s)\alpha_{s_i} - (s_j - s)\alpha_{s_j}}{\alpha_{s_i}\alpha_{s_j}(s_i - s_j)}(e^{-m} - e^{-ma})$$

where the presence of $(\sigma - 1)$ accounts for the fact that the estimation is performed on firm size data, not productivity. Given the values for σ, δ, α_{s_i}, α_{s_j}, s_i and s_j determined in section IV.E of the paper, $\tilde{g}_{s,a}$ is a function of m alone. Next, define the counterpart of $\tilde{g}_{s,a}(m)$ in the reduced form coefficients as $\beta'_{s,a} = \beta_{s,a} - \beta_{s,1}$, where $\beta_{s,a}$ denotes the schooling by age coefficients in equation (1) in the paper. Let $d_{s,a}(m) = \beta'_{s,a} - \tilde{g}_{s,a}(m)$, and stack these differences for all s and $a > 1$ into a vector $d(m)$. Let $\hat{d}(m)$ denote the vector obtained by replacing the $\beta'_{s,a}$ coefficients in $d(m)$ with their sample counterparts $\hat{\beta}'_{s,a}$. Then the minimum distance estimator is given by

$$\hat{m} = \arg\min_m \hat{d}(m)' W \hat{d}(m)$$

where W is a weighting matrix. I set $W = I$, the identity matrix, so that all coefficients receive identical weight.

The estimator $\hat{m}$ is asymptotically normal with mean equal to the true value of m and variance $\sigma_m^2 = (D'D)^{-1}D'\Omega D(D'D)^{-1}$, where $D = \frac{\partial d(m)}{\partial m}$ and Ω is the covariance matrix of the $\beta'_{s,a}$ coefficients. I estimate σ_m^2 by replacing D and Ω with their sample counterparts.

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E Appendix Tables

Table E.1: Summary Statistics

	Entrepreneur Schooling $\in [0,6)$ N=171 480					Entrepreneur Schooling $\in [6,9)$ N=193 478				
	Mean	SD	p10	p50	p90	Mean	SD	p10	p50	p90
Sales	356.7	1050.0	34.0	141.1	692.2	473.1	5448.7	36.3	150.5	792.0
Value Added	98.4	223.5	8.0	49.5	203.6	119.5	844.5	8.3	52.5	227.1
Employment	6.78	11.51	2.00	4.00	13.00	7.43	26.32	2.00	4.00	14.00
Fixed Assets	73.7	266.9	0.3	17.2	162.3	94.2	719.6	0.6	20.0	184.8
Number of Entrepreneurs	1.49	0.69	1.00	1.00	2.00	1.51	0.69	1.00	1.00	2.00
Entrepreneur Schooling	4.10	0.49	4.00	4.00	5.00	6.27	0.60	6.00	6.00	7.50
Non-Entrepreneur Schooling	5.82	2.36	4.00	5.33	9.00	6.75	2.17	4.00	6.00	9.00
Entrepreneur Experience	33.55	9.35	21.50	33.00	46.00	26.15	8.57	16.00	25.00	38.00
Non-Entrepreneur Experience	21.46	9.71	9.50	20.75	34.29	19.93	9.52	8.00	19.00	32.50
Firm Age	7.76	4.98	2.00	7.00	15.00	6.93	4.89	1.00	6.00	14.00

	Entrepreneur Schooling $\in [9,12)$ N=211 833					Entrepreneur Schooling $\in [12,15)$ N=215 033				
	Mean	SD	p10	p50	p90	Mean	SD	p10	p50	p90
Sales	506.3	3771.8	31.2	145.5	862.8	781.9	10145.5	26.5	148.5	1101.7
Value Added	121.3	710.4	3.6	46.3	231.0	163.3	1599.1	0.8	46.5	282.8
Employment	7.23	25.84	2.00	4.00	13.00	8.25	70.08	1.00	4.00	13.00
Fixed Assets	107.5	980.3	0.5	19.8	192.9	173.0	2823.0	0.5	22.3	236.7
Number of Entrepreneurs	1.38	0.65	1.00	1.00	2.00	1.31	0.84	1.00	1.00	2.00
Entrepreneur Schooling	9.17	0.51	9.00	9.00	10.00	12.18	0.60	12.00	12.00	12.00
Non-Entrepreneur Schooling	8.30	2.53	5.00	9.00	12.00	9.96	3.08	6.00	10.50	12.50
Entrepreneur Experience	22.64	9.15	11.00	22.00	35.00	17.91	8.90	7.00	17.00	30.00
Non-Entrepreneur Experience	19.25	9.92	7.00	18.33	32.50	17.43	10.18	5.00	16.00	31.14
Firm Age	5.64	4.70	1.00	4.00	13.00	5.37	4.70	0.00	4.00	12.00

	Entrepreneur Schooling $\in [15,17]$ N=172 489					All Firms N=964 313				
	Mean	SD	p10	p50	p90	Mean	SD	p10	p50	p90
Sales	1399.6	10463.7	27.0	170.8	1861.3	694.3	7207.2	30.9	149.7	1025.9
Value Added	379.5	2766.9	3.2	66.5	495.3	172.4	1487.3	4.5	50.9	275.0
Employment	11.67	66.48	2.00	4.00	18.00	8.21	46.88	2.00	4.00	14.00
Fixed Assets	714.4	11878.6	0.8	31.8	492.0	222.0	5234.3	0.5	21.5	229.3
Number of Entrepreneurs	1.34	1.37	1.00	1.00	2.00	1.40	0.88	1.00	1.00	2.00
Entrepreneur Schooling	16.72	0.68	15.00	17.00	17.00	9.71	4.30	4.00	9.00	17.00
Non-Entrepreneur Schooling	11.43	3.70	6.00	12.00	17.00	8.48	3.44	4.00	8.46	12.00
Entrepreneur Experience	13.60	8.79	4.00	12.00	26.00	22.62	11.11	8.35	22.00	38.00
Non-Entrepreneur Experience	16.23	10.52	4.00	14.44	31.00	18.83	10.13	6.00	18.00	32.33
Firm Age	5.60	4.67	1.00	4.00	12.00	6.21	4.87	1.00	5.00	13.00

Notes: This table presents summary statistics for the sample of firm-year observations in the 2004-2017 period, when both QP and SCIE data are available. Sales and value added are in thousands of 2011 euros. Employment is the number of workers reported by the firm, including entrepreneurs and non-entrepreneurs, regardless of employment status and including unpaid workers. Fixed assets is the book value of the firm's tangible and intangible assets, also in thousands of 2011 euros. Entrepreneurs are defined in section II in the paper. Entrepreneur and non-entrepreneur schooling and experience correspond to average years of schooling and potential experience for each group of workers, where experience is defined as age minus years of schooling, minus six. Firm age is based on the firm's reported year of incorporation.

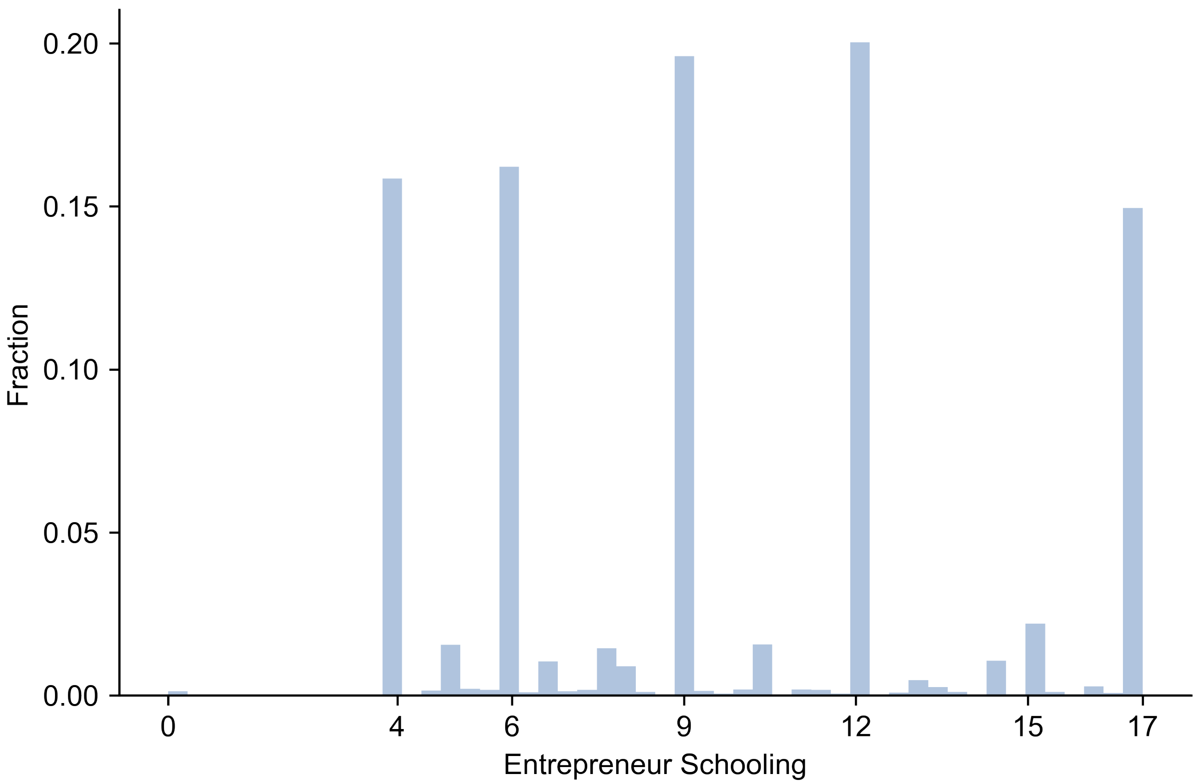
Table E.2: Entrepreneur Schooling and Firm Dynamics

	(1)	(2)	(3)	(4)	(5)	(6)
Entrepreneur Schooling ×						
Firm Age = 0	0.0206	0.0148	0.0204	0.0216	0.0206	0.0206
	(0.0030)	(0.0027)	(0.0030)	(0.0030)	(0.0215)	(0.0075)
Firm Age = 1	0.0397	0.0335	0.0394	0.0398	0.0397	0.0397
	(0.0027)	(0.0023)	(0.0026)	(0.0026)	(0.0172)	(0.0059)
Firm Age = 2	0.0526	0.0464	0.0527	0.0518	0.0526	0.0526
	(0.0027)	(0.0024)	(0.0027)	(0.0027)	(0.0168)	(0.0048)
Firm Age = 3	0.0604	0.0543	0.0604	0.0594	0.0604	0.0604
	(0.0028)	(0.0025)	(0.0028)	(0.0028)	(0.0174)	(0.0047)
Firm Age = 4	0.0643	0.0580	0.0646	0.0631	0.0643	0.0643
	(0.0030)	(0.0027)	(0.0029)	(0.0029)	(0.0179)	(0.0045)
Firm Age = 5	0.0695	0.0631	0.0694	0.0676	0.0695	0.0695
	(0.0031)	(0.0028)	(0.0030)	(0.0030)	(0.0186)	(0.0049)
Firm Age = 6	0.0704	0.0643	0.0705	0.0683	0.0704	0.0704
	(0.0032)	(0.0030)	(0.0032)	(0.0032)	(0.0191)	(0.0051)
Firm Age = 7	0.0704	0.0643	0.0705	0.0686	0.0704	0.0704
	(0.0034)	(0.0031)	(0.0033)	(0.0033)	(0.0196)	(0.0055)
Firm Age = 8	0.0720	0.0656	0.0719	0.0694	0.0720	0.0720
	(0.0035)	(0.0033)	(0.0034)	(0.0034)	(0.0195)	(0.0054)
Firm Age = 9	0.0701	0.0636	0.0702	0.0685	0.0701	0.0701
	(0.0035)	(0.0033)	(0.0035)	(0.0035)	(0.0197)	(0.0045)
Firm Age = 10	0.0702	0.0637	0.0703	0.0681	0.0702	0.0702
	(0.0036)	(0.0034)	(0.0036)	(0.0036)	(0.0193)	(0.0050)
Entrepreneur Experience	0.0258	0.0337	0.0176	0.0160	0.0258	0.0258
	(0.0026)	(0.0027)	(0.0026)	(0.0025)	(0.0040)	(0.0026)
Entrepreneur Experience^2	-0.0004	-0.0005	-0.0002	-0.0001	-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Non-Entrepreneur Schooling	-0.0039		-0.0028	-0.0032	-0.0039	-0.0039
	(0.0032)		(0.0032)	(0.0032)	(0.0088)	(0.0034)
Non-Entrepreneur Experience	0.0699		0.0713	0.0702	0.0699	0.0699
	(0.0026)		(0.0025)	(0.0026)	(0.0065)	(0.0012)
Non-Entrepreneur Experience^2	-0.0015		-0.0016	-0.0015	-0.0015	-0.0015
	(0.0001)		(0.0001)	(0.0001)	(0.0001)	(0.0000)
Log Number of Entrepreneurs			0.6118			
			(0.0210)			
N	218,713	218,713	218,713	215,669	218,713	218,713
R^2	0.105	0.082	0.128	0.103	0.105	0.105

Notes: This table reports results from estimating several versions of equation (2) in the paper for the sample of firms in the 2004-2007 cohorts. Output is measured by sales. Column four employs an alternative definition of entrepreneurship where a unique individual within each firm is identified as the entrepreneur, by taking the individual with the highest wage among those identified as entrepreneurs under the baseline definition. When there are ties in wages, I take the oldest individual, and then drop a residual number of observations where age does not break the tie. All regressions include firm age and year fixed effects. Errors are clustered at the firm level in all columns except five and six, where errors are clustered at the sector and year level respectively.

F Appendix Figures

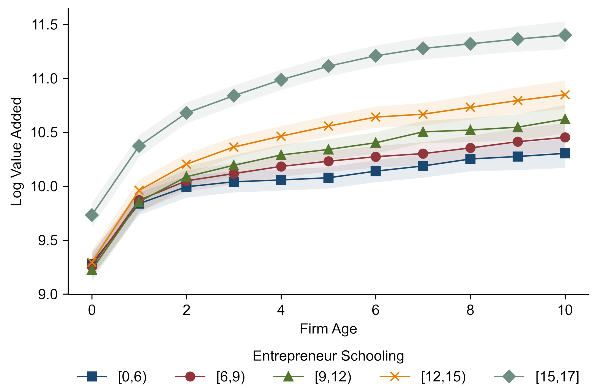
Figure F.1: Histogram of Entrepreneur Schooling



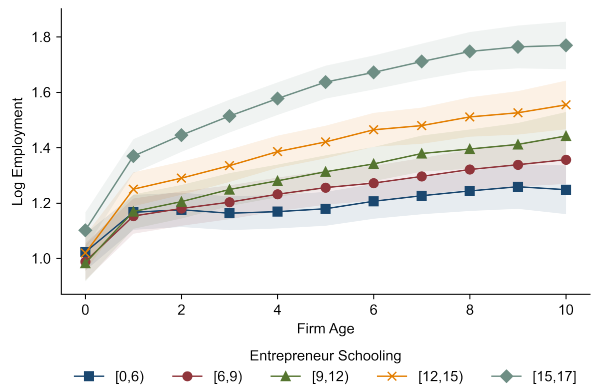
Notes: This figure plots a histogram of average entrepreneur schooling for the sample of firm-year observations in the 2004-2017 period. The five points at which most firms are concentrated correspond to the five main education levels reported in the data: 4th grade, 6th grade, 9th grade, 12th grade and the *licenciatura* higher education degree.

Figure F.2: Other Outcomes for the 2004-2007 Cohorts

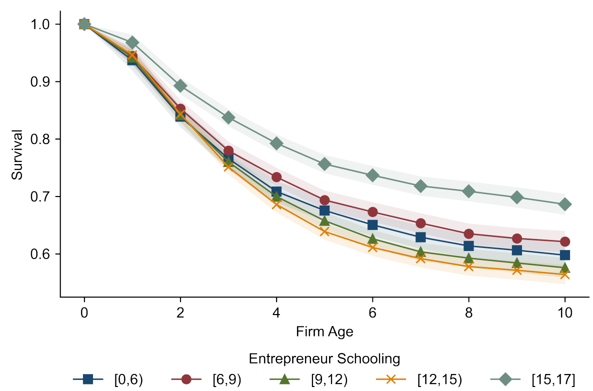
(a) Value Added



(b) Employment



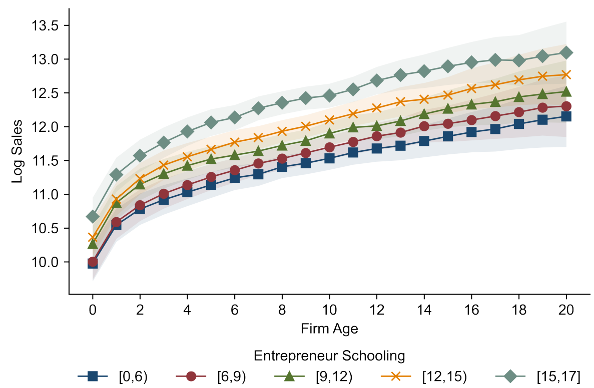
(c) Survival



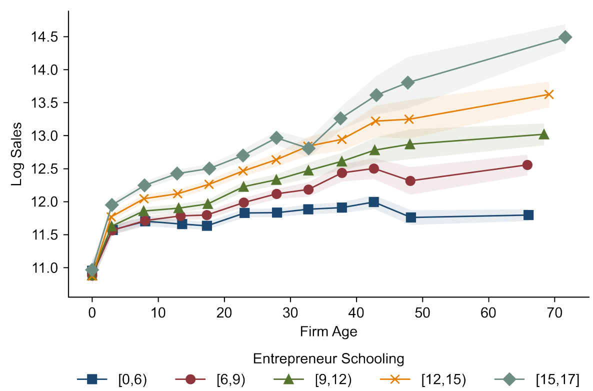
Notes: These figures plot entrepreneur schooling group by firm age coefficients from estimating equation (1) in the paper for all firms up to age 10 in the 2004-2007 cohorts, when the outcome is value added, employment or cumulative survival rates. The shaded areas represent 95% confidence intervals. Standard errors are clustered at the firm level.

Figure F.3: Firm Life Cycle Dynamics for Other Samples

(a) Sales in the 1995-1997 Cohorts

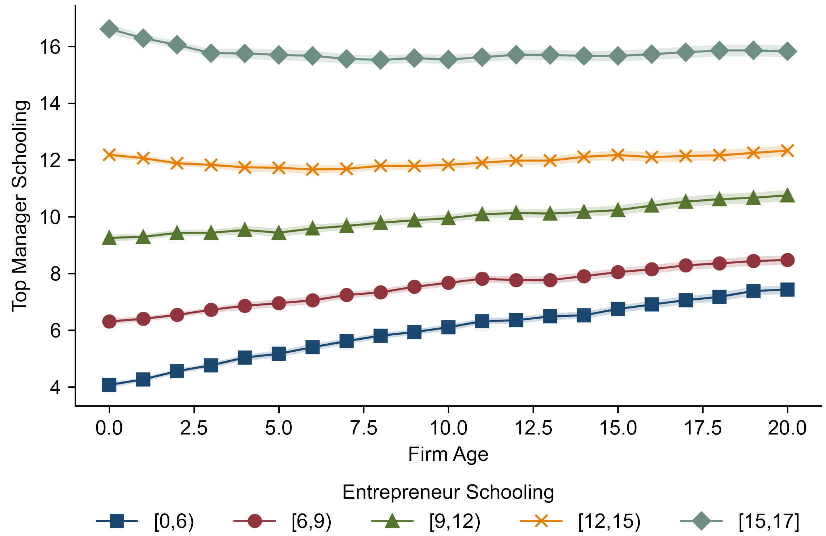


(b) Sales in the 2017 Cross-Section



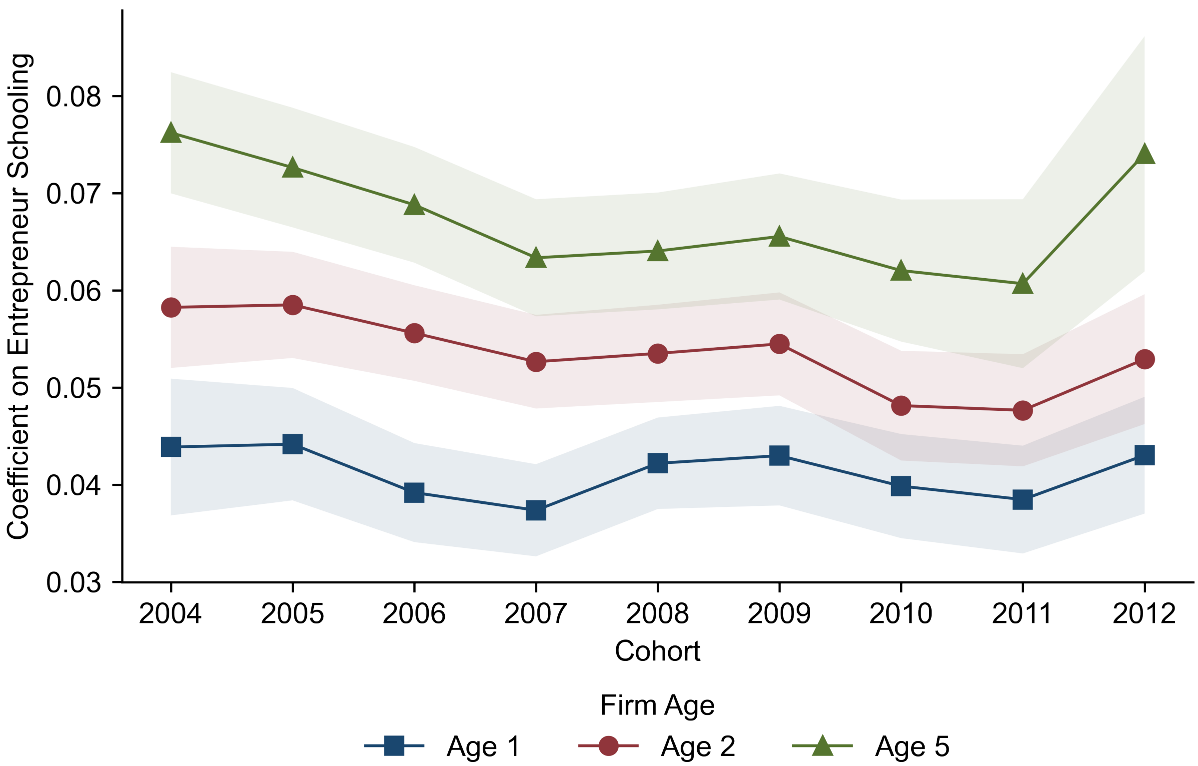
Notes: These figures plot entrepreneur schooling group by firm age coefficients from estimating equation (1) in the paper. Panel a) includes firms up to age 20 in the 1995-1997 cohorts, and panel b) includes all firms in the 2017 cross-section. Output is measured by sales. In panel b), I use the education of the first top managers observed in the data to proxy for entrepreneur schooling when firms are not observed from entry, and firms are grouped into 5-year age bins, plus a separate bin for entrants and one for all firms 50 or older. The shaded areas represent 95% confidence intervals. Standard errors are clustered at the firm level.

Figure F.4: Persistence of Top Manager Schooling in the 1995-1997 Cohorts



Notes: This figure plots average top manager schooling by firm age for surviving firms in the 1995-1997 cohorts up to age 20, sorting firms into five groups by average entrepreneur years of schooling. The shaded areas represent 95% confidence intervals.

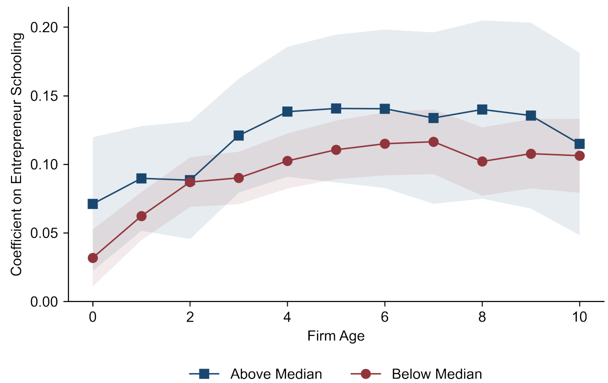
Figure F.5: Cohort-by-Age Coefficients



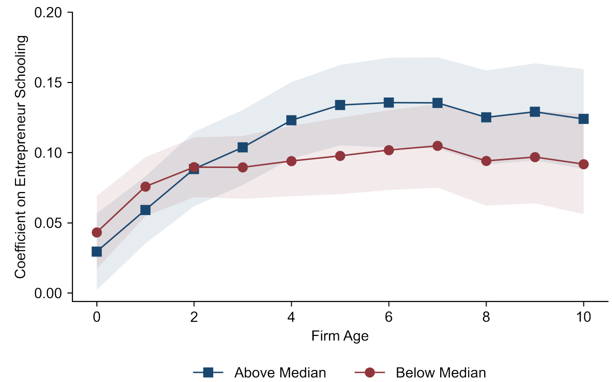
Notes: This figure plots cohort-specific schooling-by-age coefficients from estimating (2) in the paper with the schooling-by-age terms interacted with cohort indicators, for all firms up to age 5 in the 2004 to 2012 cohorts. Output is measured by sales. I include sector-by-year fixed effects to account for differences in sector composition across cohorts. The shaded areas represent 95% confidence intervals. Standard errors are clustered at the firm level.

Figure F.6: Sector Heterogeneity: Additional Evidence

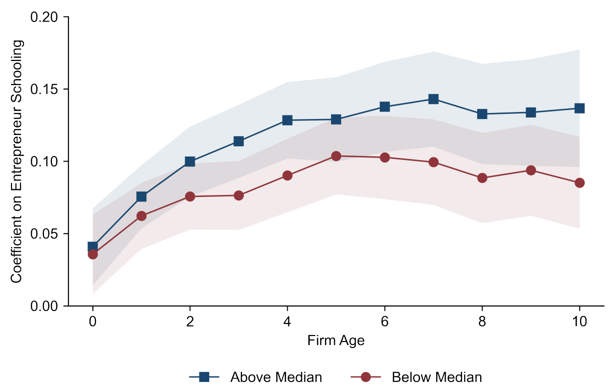
(a) Human Capital Intensity



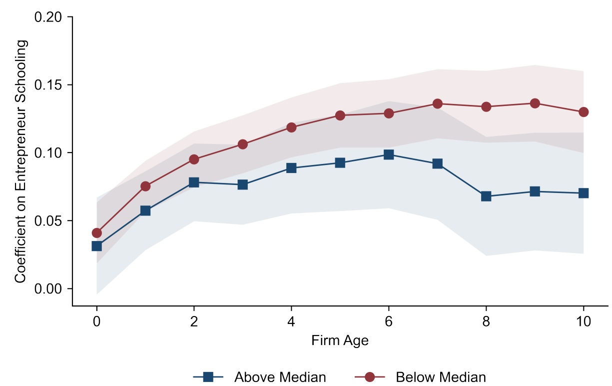
(b) External Finance Dependence



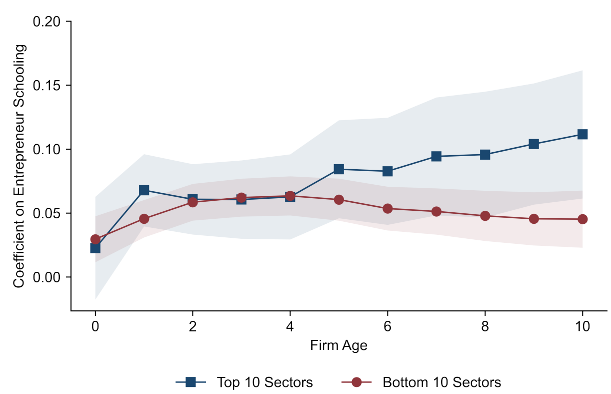
(c) Contract Intensity



(d) Physical Capital Intensity

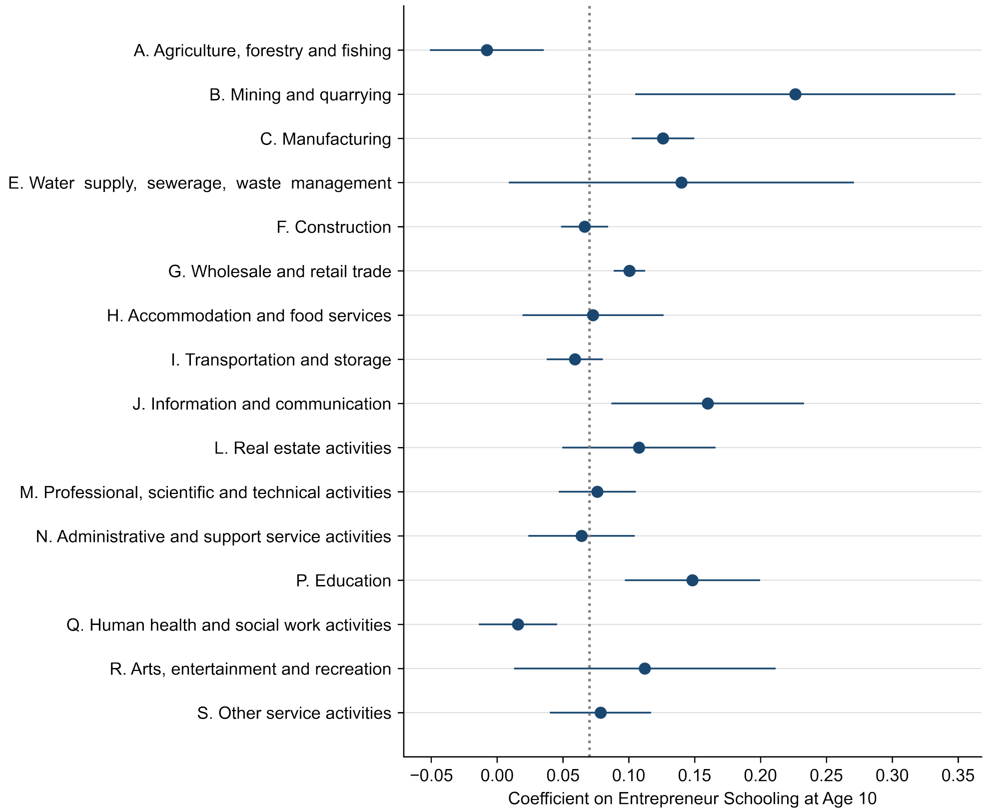


(e) Social Network Intensity



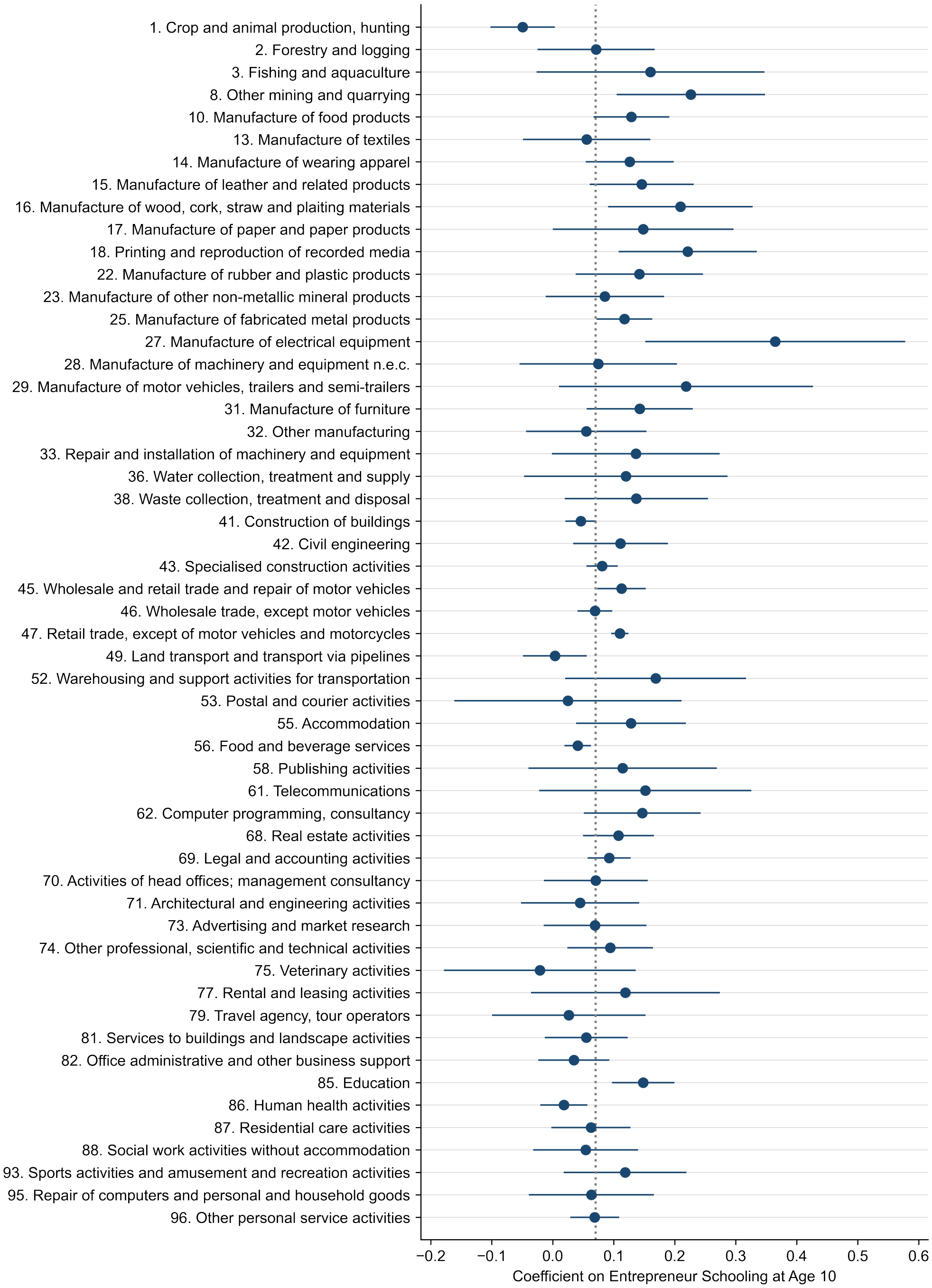
Notes: This figure plots schooling-by-age coefficients from estimating equation (2) in the paper on sales data separately for above and below median sectors along five different dimensions: human capital intensity (Ciccone and Papaioannou, 2009), external finance dependence (Rajan and Zingales, 1998), contract intensity (Nunn, 2007), physical capital intensity, and social networks intensity (Fracassi, 2017). All regressions include 5-digit sector-by-year fixed effects. Data on external financial dependence is from Kroszner, Laeven and Klingebiel (2007), who reconstruct the Rajan and Zingales (1998) measure at the 3-digit ISIC level. Data on physical capital intensity is from Bartelsman and Gray (1996), as reported in Ciccone and Papaioannou (2009). Fracassi (2017) only reports the top 10 and bottom 10 sectors by social network intensity, so I use this instead of above and below median sectors. The shaded areas represent 95% confidence intervals. Standard errors are clustered at the firm level.

Figure F.7: Sector Heterogeneity: 1-letter Sector Estimates



Notes: This figure plots schooling coefficients at age 10 and the corresponding 95% confidence intervals from estimating equation (2) in the paper on sales data separately by 1-letter sector. The dashed line corresponds to the average coefficient across sectors estimated in the overall sample. Besides financial and insurance activities, which are not covered by SCIE, the figure excludes the utilities sector, which has a small number of observations (0.03% of the sample) and hence a wide confidence interval, for clarity. Standard errors are clustered at the firm level.

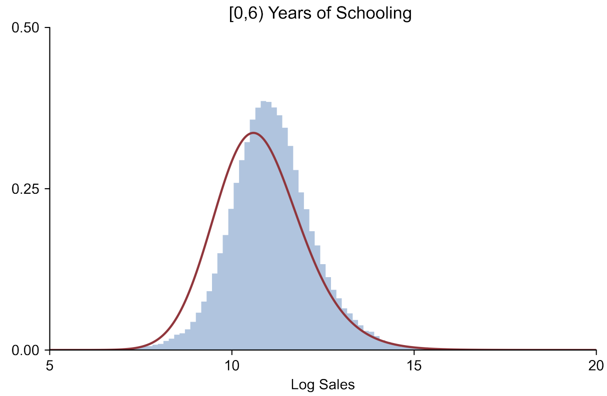
Figure F.8: Sector Heterogeneity: 2-digit Sector Estimates



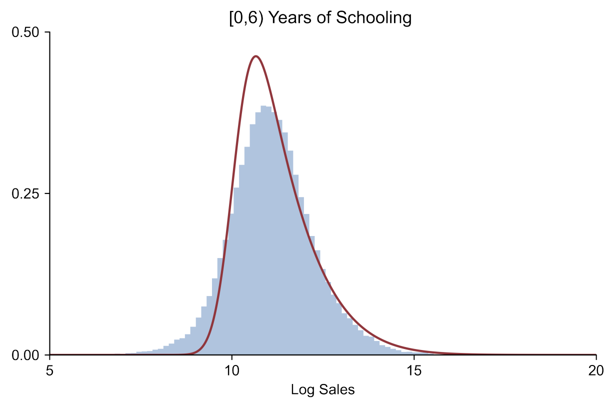
Notes: This figure plots schooling coefficients at age 10 and the corresponding 95% confidence intervals from estimating equation (2) in the paper on sales data separately by 2-digit sector. The dashed line corresponds to the average coefficient across sectors estimated in the overall sample. I exclude a set of small sectors with wide confidence intervals for clarity, namely motion pictures, TV and music, creative arts and entertainment, employment activities, security and investigation, chemicals, information services, water transport, basic metals, beverages, other transport equipment, utilities, scientific research and development, pharmaceuticals and sewerage. Together these sectors represent 1.3% of the sample. Standard errors are clustered at the firm level.

Figure F.9: Sales Distributions: Data and Restricted Models

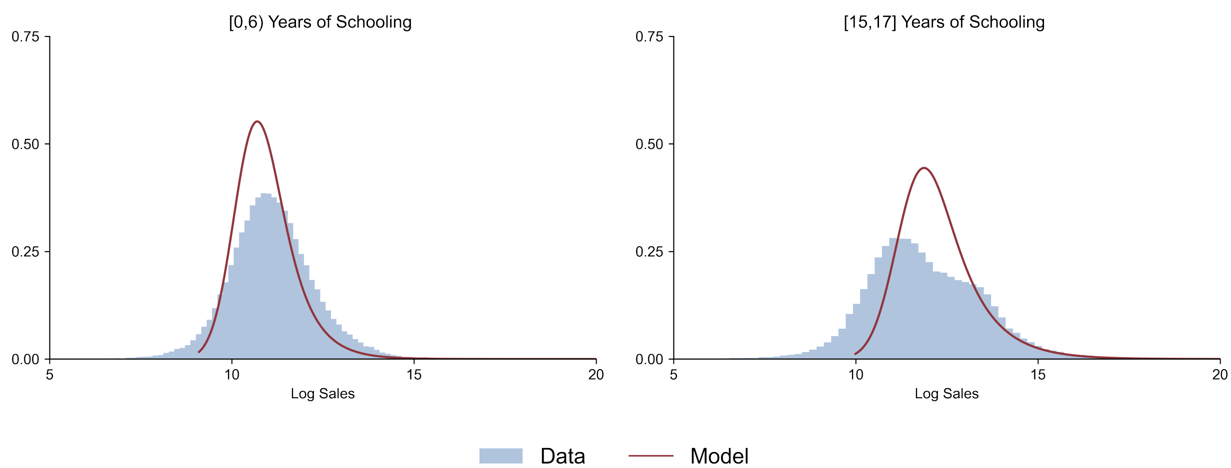
(a) $\sigma_r = 0$



(b) $\sigma_\epsilon = 0$



(c) $\sigma_\eta = 0$



Notes: This figure plots histograms of log sales in the sample and densities of log sales estimated from restricted versions of the model for the top and bottom entrepreneur schooling groups. The parameters σ_r, σ_ϵ and σ_η are constrained to equal zero in panels a), b) and c) respectively. Model-implied densities are evaluated at the mean of entrepreneur schooling in the sample within each group. In the model with $\sigma_\epsilon = 0$, a residual number of observations of entrepreneurs with no schooling are dropped from the estimation, since equation (16) in the paper cannot be evaluated for these cases.