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Abstract

We document that individuals who grew up in areas with high density of firms are more likely, as adults, to become entrepreneurs, controlling for the density of firms in their current location. Conditional on becoming entrepreneurs, the same individuals are also more likely to be successful entrepreneurs, as measured by business income or firm productivity. Strikingly, firm density at entrepreneur's young age is more important than current firm density for business performance. These results are not driven by better access to external finance or intergenerational occupation choices. They are instead consistent with entrepreneurial capabilities being at least partly learnable through social contacts. In keeping with this interpretation, we find that entrepreneurs who at the age of 18 lived in areas with a higher firm density tend to adopt better managerial practices (enhancing productivity) later in life.

Key Words: Entrepreneurship, learning, spillovers.

JEL classification numbers: J24, M13, R11.

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1 Introduction

Who becomes an entrepreneur? The answer economists give to this question is that individuals choose their occupation by comparing the costs and benefits of alternative jobs. In the classical Lucas (1978)/Rosen (1982) model of occupational choice, individuals with greater managerial skills - defined as the ability to extract more output from a given combination of capital and labor - will sort into entrepreneurship because the return from managing a firm exceeds the wage they can earn working as employees. Entrepreneurial skills can be interpreted more broadly to include, for instance, the ability to manage (and stand) risk, and the capacity to identify and assess the economic potential of a new product or process. While it remains unclear how people obtain these skills, it is important to understand whether such skills are innate characteristics or are instead acquired through learning - and if so, how.

Distinguishing between these two sources of entrepreneurial skills (i.e., innate or learned) is of practical importance. If entrepreneurial ability is innate, then its distribution should not differ substantially across populations and much of the observed differences in entrepreneurship across countries or regions within countries should be traced back to factors that facilitate or discourage people with entrepreneurial abilities to set up a firm - such as the availability of capital. Fostering entrepreneurship then requires removing these obstacles. If instead managerial abilities can be acquired through learning, differences in entrepreneurship can partly reflect differences in learning opportunities across countries or regions and the constraints to entrepreneurship are induced by learning frictions. Fostering entrepreneurship requires improving the learning process.

In this paper we investigate whether selection into entrepreneurship and entrepreneurs' success are affected by learning opportunities. While individuals can learn how to become an entrepreneur and how to be a successful one in a variety of ways (e.g., from parents, friends, schools, etc.) and at different stages of their life cycle, we look at one specific channel: learning from one's environment during formative years (adolescence). Arguably, for a young individual growing up in Silicon Valley it should be easier than elsewhere to learn how to set up and run a firm because the high concentration of entrepreneurial activities in the area provides many direct or indirect learning opportunities. We study whether these intuitive predictions receive empirical support. In particular, we test whether firm density in the location where individuals grow up affect the choice of becoming an entrepreneur and their subsequent performance as an entrepreneur.

We study these questions using a variety of data sets. The first is a sample of Italian entrepreneurs actively managing a small incorporated firm (the *Associazione Nazionale delle Imprese Assicurative,* or ANIA sample). Besides a rich set of demographic variables, it contains detailed information on the entrepreneurs' place of birth, current location, and location at age 18 (which we term the "learning age"). We match these entrepreneurs with their firms' balance sheet data and thus obtain measures of firm total factor productivity and sales per worker. This allows us to test one of the implications of the learning ability model: firms' productivity should be increasing with the firm density of the location in which the entrepreneur lived at learning age, controlling for *current* density. Because this dataset only includes entrepreneurs, it cannot be used to test the other implication of the learning model, i.e., that all else equal, learning opportunities should increase the odds of selecting into entrepreneurship. A second dataset we use (the *Survey of Household Income and Wealth*, or SHIW sample) addresses this problem. SHIW contains data for a representative sample of the Italian population, reporting, for each participant in the survey, type of occupation, demographics (including current place of residence and birth) and data on personal income distinguished by source - such as income from entrepreneurial activity. However, it has no detailed information on the firm these people work for or manage (besides size). Hence, the two dataset nicely complement each other. Finally, to investigate further and more directly which entrepreneurial abilities are learned through exposure to other firms earlier in life, we supplement the ANIA survey with measures of managerial practices collected using the methodology pioneered by Bloom and Van Reenen (2010b). If exposure to a larger set of firms allows one to learn superior managerial practices, then entrepreneurs who grew up in high firm density locations should adopt better managerial practices.

Consistent with the learning model, we find that individuals who grew up in a location with a higher entrepreneurial density (ED henceforth) are indeed more likely to become entrepreneurs. This result holds independently of whether we use a broader definition of entrepreneur (one that also includes the self-employed) or a narrower one that only features individuals running an incorporated business. Our finding holds while controlling for the firm density in the current location (reflecting thick-market externalities), for measures of current access to external finance in the local market where the firm is located and in the location at learning age, and for having parents who are entrepreneurs themselves. The effect is sizable. With the broader definition of entrepreneur, one standard deviation increase in ED at learning age increases the likelihood of becoming an entrepreneur by 1.5 percentage points, around 8% of the sample mean.

When we look at variation in performance among entrepreneurs, we find that those who faced a higher firm density at learning age earn a higher income from their business. This finding is consistent with the idea that entrepreneurial abilities can be acquired and that acquisition occurs through exposure to a richer entrepreneurial environment. A one standard deviation increase in firm density at learning age results in a 8% higher income. Because the SHIW only reports where a person was born and where he currently lives, this result is obtained under the assumption that an individual at learning age was located in the same place where he was born, thus inducing some measurement error in the firm density at learning age.[1] The other sample is free from this problem and, in addition, it allows to construct measures of firms productivity. In this sample we find that firms run by entrepreneurs who faced a higher firm density at learning age have currently a higher total factor productivity and higher output per worker. Remarkably, the elasticity of entrepreneurial quality to ED is very close in the two datasets, although the sample and the variables used are different.

In our data set there are two reasons why individuals living in a given province were exposed at learning age to different learning opportunities. First, they are of different age. Second, they grew up in different places. Hence, identification relies on two sources of variation: (a) differences over time in firm density for people of different ages currently living in the same province where they grew up (stayers); (b) cross-province differences in firm density for people of the same age who grew up in a different province from the one in which they currently live (movers).[2] As we will show, focusing on the sample of movers addresses a series of endogeneity issues that can arise from the serial correlation in current ED and ED at learning age for entrepreneurs that did not move. In fact, our results are even stronger when focusing on the sample of movers. Finally, the two sources of variability also allow us to test for, and dismiss, the possibility that our ED indicator is proxying for other potential determinants of entrepreneurship, in particular genetic differences across locations.

The final question we address is which aspects of entrepreneurship are more prone to be learned. Modern literature on entrepreneurship argues that being an entrepreneur requires a variety of skills.[3] Classical theories of entrepreneurship stress the role of personal traits, in terms of the ability to innovate (Schumpeter, 1911) and to bear uncertainty and risk (Knight, 1921; Kihlstrom and Laffont, 1979). These features of entrepreneurship probably have an

[1]This measurement error is likely to be small; from the ANIA dataset we calculate that 85% of people born in a given province are still in that province at learning age.

[2]An Italian province is an administrative unit approximately equivalent to a US county.

[3]For example, Lazear (2005) shows that MBAs with a more balanced set of skills (lower variance in exam grades) are more likely to become entrepreneurs.

important innate component and it is still unclear to what extent they can be learned. On the other hand, managerial capabilities are more likely to be learned. We therefore test whether entrepreneurs who grew up in high firm-density provinces adopt better managerial practices and develop traits that are traditionally associated with entrepreneurship. We find some evidence that entrepreneurs who grew up in high firm-density locations adopt better managerial practices, although the effect is not precisely estimated. On the other hand, we find no evidence that exposure to firms at learning age affects the traits that have been traditionally associated with entrepreneurship, such as risk aversion, aversion to ambiguity, self-confidence and optimism. These traits are either learned early in life, possibly within the family (Dohmen et al., 2012), or are innate. Finally, we find no evidence that entrepreneurial density at learning age affects innovation capacity, suggesting that this key aspect of entrepreneurship is also less prone to learning.

The rest of the paper proceeds as follows. In Section 2 we relate our work to the vast literature on entrepreneurship. In Section 3 we lay down a simple model of entrepreneurial choice allowing for learning and obtain two testable predictions: higher learning opportunities shift to the right the initial distribution of entrepreneurial talent, and a) increase the chance that an individual becomes an entrepreneur; and b) raise the ability of those who select into entrepreneurship. We also discuss how to operationalize opportunities to learn entrepreneurial ability. In Section 4 we discuss our identification strategy, while Section 5 presents the data. Results are shown in Section 6, first for the SHIW and then for the ANIA sample. Section 7 shows the evidence on managerial practices and traits, and Section 8 concludes.

2 Relation to the Literature

There is a vast literature on the determinants of the choice to become an entrepreneur and of entrepreneurial success.[4] Our approach, relating entrepreneurial outcomes to the entrepreneurial density in the location where the would-be entrepreneur was living when young, adds to several current debates in entrepreneurship.

First, we contribute to the literature on the determinants of occupational choice. There is clear evidence that offspring of entrepreneurs are more likely to become entrepreneurs than offspring of employees. Parker (2009) surveys this literature and distinguishes among five hypotheses: (i) inheritance of the family business; (ii) relaxation of liquidity constraints; (iii) learning general entrepreneurial skills; (iv) industry- or firm-specific skills, possibly including

[4]See Parker (2009) for a comprehensive survey.

access to the business network of parents; and (v) correlated preferences between parents and their offspring, possibly enhanced by role modeling. He concludes that the evidence supplies some support for hypotheses (iii), (iv), (v), consistent with the idea that entrepreneurship is at least partially transmittable and, possibly, learnable. Of course, intergenerational correlations in occupational choice do not distinguish between the genetic and the social component of parent-offspring transmission of entrepreneurial attitudes. Some recent work has addressed this issue using twin studies.[5] Lindquist, Sol, and Van Praag (2015) use adoptees to test the role of nature versus nurture in transmitting entrepreneurship. They show that the effect of the adoptive parents are twice as large as those of the biological parents. Other twin studies confirm a larger role of "nurture" relative to "nature" in determining the choice to become an entrepreneur (Nicolaou et al., 2008; Zhang et al., 2009; Nicolaou and Shane, 2010). Our work contributes to this literature by showing that not only the family, but also the local economic environment in which a person grows up affects the choice to become an entrepreneur. We show that growing up in a high *ED* area contributes to the acquisition of entrepreneurial skills, which increases the supply of entrepreneurs.

An alternative channel through which *ED* may affect the supply of entrepreneurs is role modeling: in high *ED* areas individuals may develop a taste for being an entrepreneur. Lindquist, Sol, and Van Praag (2015) find that the intergenerational transmission is stronger if parent and offspring are of the same gender, a fact that they interpret in terms of role modeling. Needless to say, role modeling can also be transmitted through the social environment and could explain our findings on the likelihood of becoming an entrepreneur. However, in itself it cannot explain the higher ability of entrepreneurs who grew up in denser areas. If anything, role modeling should encourage relatively less able individuals to become entrepreneurs, thus lowering the average ability of entrepreneurs.

There is also a growing literature that studies the effects of networks on entrepreneurship, reviewed among others in Hoang and Antoncic (2003). Most of this work finds that local networks do help entrepreneurial activity. Michelacci and Silva (2007) attribute to the importance of local networks the fact that entrepreneurs tend to be less mobile than employees. Compared to this work, we show that the *ED* one is exposed to when young remains a significant determinant of entrepreneurial success in adulthood. This holds after controlling for current *ED* and even among movers, for whom the original network is less likely to have an independent effect today. This implies that the network effect is not

[5]See Sacerdote (2011) for a recent survey.

confined to supplying useful inputs today (i.e., knowledge spillovers, information dissemination and thus easier access to credit, customers, inputs) but also contributes to improve the entrepreneurial ability. In fact, its effects survive even when severed from the network itself. This idea is confirmed by some recent work on return immigrants, who are more likely than non-migrants to start a business even if they have lost access to their original social network while overseas (Wahba and Zenou, 2012).

We also contribute to the vast literature on local externalities (Cingano and Schivardi, 2004; Duranton and Puga, 2004b; Rosenthal and Strange, 2004b). In particular, our approach singles out one specific external effect: learning from others. Within the entrepreneurship literature, Glaeser, Kerr, and Ponzetto (2010) document that area-sectors with lower average initial firm size record higher employment growth in subsequent years. They show that the evidence is consistent with heterogeneity in both entry costs and in the supply of entrepreneurs. We find evidence for the second motive and provide an explanation for it: in areas with more firms to begin with it is easier to accumulate entrepreneurial skills. The paper that is closer to ours is De Figueiredo, Meyer-Doyle, and Rawley (2013), who study "inherited agglomeration effects", defined as human capital that managers acquire while working in an industry hub that may be transferred to a spinoff. They concentrate on the hedge fund industry and show that hedge fund managers that previously worked in London or New York outperform those who did not in terms of financial returns on their portfolio. Like us, they find that inherited agglomeration effects are at least as large as traditional, contemporaneous agglomeration effects. Differently from us, they work on a single industry, focus on managers rather than entrepreneurs and do not study occupational choice. Giannetti and Simonov (2009) study the correlation between entrepreneurial density at the municipality level and the propensity to become an entrepreneur, finding a positive correlation after accounting for a large set of potentially correlated effects. Differently from us, they correlate entrepreneurial outcomes with current density, rather than density at learning age. Their strategy is therefore unable to separate learning effects from other contemporaneous spillovers.

Methodologically, our approach is related to a small labor/geography literature on wage city premia. Glaeser and Maré (2001) first showed that a fraction of the urban wage premium - the extra wage that workers earn when moving to a city– stays with them when they move back to a rural area. They interpret this as evidence that workers accumulate human capital while in cities. This evidence based on US data has been confirmed and extended by De la Roca and Puga (2013) for Spain and Matano and Naticchioni (2012) for

Italy. Compared to these papers, we focus on entrepreneurs and consider a specific period of life in which learning should be particularly important. Moreover, we use ED as an indicator of learning opportunities, rather than densely versus sparsely populated areas.[6]

3 Learning, Entrepreneurial Ability and Occupational Choice

In this section we provide a simple analytical framework to analyze the effects of heterogeneity in learning possibilities across locations and then discuss our measure of learning opportunities.

3.1 Modelling Learning Opportunities

We use the occupational choice model of Lucas (1978), as modified by Guiso and Schivardi (2011), to allow for multiple locations and an entry cost. We illustrate the model briefly to derive some empirical predictions and refer the interested reader to Guiso and Schivardi (2011) for details. The economy is comprised of N locations, each with a unit population of workers who can choose to be an employee at the prevailing wage or become an entrepreneur. An entrepreneur combines capital and labor to produce output with a decreasing returns to scale technology and is the residual claimant. As such, entrepreneurial income is:

$$\pi(x) = xg(k, l) - rk - wl - c \tag{1}$$

where x is entrepreneurial ability, k capital, l labor, r the rental price of capital, w the wage and c a fixed entry cost. The rental price and the wage are equalized across locations. Entrepreneurial talent is drawn from a random variable $\widetilde{x}$ distributed according to a distribution function $\gamma(x, \lambda_i)$ over the support $(\underline{x}, \overline{x})$, $0 \leq \underline{x} < \overline{x} \leq \infty$, with corresponding cumulative distribution function $\Gamma(x, \lambda_i)$, $i = 1, ..., N$. The parameter λ is a shifter of the distribution of talent. It represents the learning opportunities that characterize each location.[7] We assume that $\partial\Gamma/\partial\lambda < 0$: λ shifts the probability distribution to the right in the first order stochastic dominance sense. Hence, individuals who grow up in a high λ region have higher entrepreneurial talent.

As in Lucas (1978), the model implies that individuals with ability above a given threshold will become entrepreneurs, as entrepreneurial profits monotonically increase with abil-

[6] The importance for long-term outcomes of the place in which individuals grow up is confirmed by recent work of Chetty and Hendren (2015), showing that growing up in a better neighborhood in the US has a strong positive impacts on various outcomes, ranging from education and income to teenage birth rates and marriage rates.

[7] Of course, λ might be any shifter of the distribution of talents. Distinguishing learning from other possible explanations will be the main task of the empirical analysis.

ity. Given a threshold z, the probability of becoming an entrepreneur is prob$(x > z) = 1 - \Gamma(z, \lambda)$. Since:

$$\frac{d(1-\Gamma(z,\lambda))}{d\lambda} = -\frac{\partial\Gamma(z,\lambda)}{\partial\lambda} > 0. \tag{2}$$

equation (2) implies that it is more likely that an individual turns to entrepreneurship in regions with higher λ. This simply states that where there are more learning opportunities, and therefore entrepreneurs are on average more capable, more people will become entrepreneurs.

Implication 1 *The probability that an individual chooses to become an entrepreneur is increasing in λ.*

The average entrepreneurial ability is the expected value of x conditional on being an entrepreneur:

$$E(x|z,\lambda) = \frac{\int_z^{\overline{x}} x\gamma(x,\lambda)dx}{1-\Gamma(z,\lambda)}. \tag{3}$$

The effect of a change in λ on average entrepreneurial quality is:

$$\frac{dE(x|z,\lambda)}{d\lambda} = \frac{[\int_z^{\overline{x}} x\frac{\partial\gamma}{\partial\lambda}dx - E(x|z,\lambda)\frac{\partial(1-\Gamma(z,\lambda))}{\partial\lambda}]}{(1-\Gamma(z,\lambda))} \tag{4}$$

The effect of a shift in the ability distribution cannot be signed a priori, as it depends on the distribution function of ability. However, $\frac{dE(x|z,\lambda)}{d\lambda} > 0$ holds for a general family of distributions: the log-concave distributions (Barlow and Proschan, 1975).[8] This family of distributions includes, among others, the uniform, the normal and the exponential. For such distributions, a positive correlation between the share of entrepreneurs and their average quality will emerge. Guiso and Schivardi (2011) show that this is indeed the case in the data. Hence, we assume this condition holds and derive our second implication.

Implication 2 *Average entrepreneurial quality increases in λ.*

It is also immediate to show that the same conclusion holds for any monotonic transformation of x. Given that profits are strictly increasing in x, from Implication 2 immediately follows:

Implication 3 *Average entrepreneurial income increases in λ.*

To sum up, a Lucas-type model of occupational choice implies that individuals that can more easily learn entrepreneurial abilities are more likely to work as entrepreneurs and, conditional on doing so, to manage more productive firms and earn higher income.

[8] A function $h(x)$ is said to be log-concave if its logarithm $\ln h(x)$ is concave, that is if $h''(x)h(x) - h'(x)^2 \leq 0$.

3.2 Entrepreneurs as Data Points

In order to test these implications we need an operational measure of $\lambda-$ the opportunities to learn entrepreneurial abilities. For this we assume that individuals growing up in different locations also face different learning environments because locations differ in the density of entrepreneurs active at a given point in time. Individuals who grow up in locations that are rich in firms (and entrepreneurs) have more opportunities to learn from the experiences of other entrepreneurs, as part of their socialization process, compared to individuals who grow up in locations lacking entrepreneurs. The idea that individuals acquire entrepreneurial capabilities from interacting and growing up among entrepreneurs is consistent with an expanding literature showing that individual traits, besides being transmitted through parenting, are acquired through socialization (Bisin and Verdier, 2001), especially through group socialization. Indeed, one strand of literature led by Hurrelmann (1988) and particularly Harris (2011), argues that interactions with peers dominate interactions with parents in the process of learning and personality formation. Furthermore, because group interactions develop with age and become increasingly intense as young individuals start branching off from the restraints of their parents, these theories imply that the acquisition of entrepreneurial capabilities through social learning should peak when young individuals are in their late teens. Empirically, we will identify this age around 18 (which we label the "learning age") and proxy learning opportunities with the density of entrepreneurs in the area where individuals lived at their learning age.

Entrepreneurial density at learning age as a measure of learning opportunities captures the idea that it is easier to listen to/observe directly entrepreneurs' experiences with success and failures and thus learn both what leads to success and how to avoid mistakes that lead to failure. It is consistent with the Chinitz (1961) effect who first documented that entry of new firms is more likely where a high number of small businesses is present. Our empirical strategy is also consistent with the plausible idea that there are stages of learning through socialization characterized by different contents about what is learned. For our purpose, the formative years – those that define what an individual would like to be and what she can become as an adult – belong in the 18-year-old age bracket (Erikson, 1968). Feedback from other entrepreneurs concerning the content of their work, the requirements to succeed in doing it, the type of life one can expect from selecting an entrepreneurial job, "role modeling", etc., can be critical at this age. How important it is may depend on the number of learning points an individual is exposed to.

Even if some entrepreneurial traits can be learned, not necessarily all can be learned in the same measure. Entrepreneurship requires several ingredients:

a) the ability to produce ideas, which may have both innate and learnable components;

b) the capital to implement the idea, which can be inherited or can be raised in the market. If capital is raised, one needs to know how to obtain it, how to identify a potential pool of investors and how to "sell" the idea to them. This capability can be learned, possibly from other entrepreneurs;

c) ability to stand risk. Twin studies show that bearing risk has a large innate component but may also have a shared environmental component due to upbringing, albeit small (Cesarini et al., 2009). People's willingness to bear risk also includes knowledge of how to manage risk when it arises, which can be learned possibly from the experiences of others. This is probably more true when decisions entail uncertainty (in the sense of Knight, 1921). Uncertainty can be dispelled through learning and knowing how to dispel it helps avoid its main consequence, leading individuals to opt for the uncertainty-free alternative, a job as an employee, when faced with an ambiguous entrepreneurial prospect;

d) ability to assemble factors of production in an efficient way, which requires organizational skills - the type of skills emphasized in our version of the Lucas (1978) model discussed above. While there could be an innate component, organizational skills can arguably be acquired most easily through either socialization or organized learning, such as participation in an MBA program;

e) finally, entrepreneurial jobs require the ability to put in effort, the persistence to pursue an objective, and (most likely) a positive or optimistic attitude.

Potentially all these ingredients can be acquired, though not necessarily to the same degree. We take no *a priori* stance on which characteristics of entrepreneurship can be learned early in life, but offer instead some evidence of what is learned by being exposed to a "thicker" entrepreneurial environment.

4 Identifying Learning Effects

Our empirical strategy consists in showing that growing up in an area with higher entrepreneurial learning opportunities (as measured by the number of firms per capita, the variable entrepreneurial density – ED – below) is associated with a higher likelihood of becoming an entrepreneur as well as better entrepreneurial outcomes later in life. We now discuss the main empirical challenges we face in bringing this prediction to the data.

Our empirical framework is based on regressions of the form:[9]

$$Y_{it} = \alpha + \beta ED_{j(i,t_L)t_L} + \gamma ED_{j(i,t)t} + \varepsilon_{it} \tag{5}$$

where Y_{it} is an entrepreneurial outcome for individual i in year t (being an entrepreneur or a measure of entrepreneurial ability/success), $t_L < t$ is the year in which individual i was 18 (the learning age), $ED_{j(i,s)\tau}$ is year τ's firms per capita in the location j in which individual i was living in year s, and ε_{it} an error term.

The role of current firm density ($ED_{j(i,t)t}$) in this regression is well known from the literature on local externalities and agglomeration economies.[10] The role of firm density at learning age ($ED_{j(i,t_L)t_L}$) is instead the channel we emphasize in this paper (learning entrepreneurial skills in the early phase of one's professional life) and in our framework it may exist over and above that of $ED_{j(i,t)t}$. Naturally, an empirical challenge is that the effect of $ED_{j(i,t_L)t_L}$ may be hard to identify separately from that of $ED_{j(i,t)t}$ given the persistence in the spatial agglomeration of firms. There are two distinctive features of our approach which give identifying power. First, young-age learning externalities can be distant in the time dimension from current externalities, which is of course especially true for older entrepreneurs. Second, some individuals currently live in locations that are different from those in which they grew up (movers), spatially breaking the link between $ED_{j(i,t_L)t_L}$ and $ED_{j(i,t)t}$. In addition to using the overall sample, we will also run regressions on the sample of movers to provide a more compelling identification of the effect of entrepreneurial learning opportunities on entrepreneurial outcomes.

A more complicated issue is the possibility that unobserved factors that explain an entrepreneur's success also explain a large share of firms in a given area, i.e., $ED_{j(i,t)t}$ is potentially correlated with ε_{it}. For example, a well functioning local financial system might be able to lower entry barriers and at the same time screen the best entrepreneurial projects. Given that $ED_{j(i,t)t}$ is strongly serially correlated, any bias induced by this particular form of endogeneity will transmit also to our effect of interest (the effect of $ED_{j(i,t_L)t_L}$ onto Y_{it}). We do not have instrumental variables that may explain differences in geographical agglomeration of firms and are uncorrelated with unobservable determinants of firm success. Instead, we adopt two empirical strategies to address this issue. The first is to have a rich

[9] For notational simplicity we omit the vector of additional controls used in all regressions. These are discussed later.

[10] For surveys of this literature, see Duranton and Puga (2004a), Rosenthal and Strange (2004a), Moretti (2011).

set of controls (including demographics, geographical controls, intergenerational variables, and controls for both current and past local credit market development), which in principle minimizes the set of unobservables that may potentially be correlated with current firm density. The second is, again, using the sample of movers. If provinces had purely idiosyncratic dynamics in firm density, the endogeneity bias induced by the correlation between $ED_{j(i,t)t}$ and ε_{it} would not "transmit" to the effect of $ED_{j(i,t_L)t_L}$ onto Y_{it} in a sample of movers (because $j(i,t_L) \neq j(i,t)$). However, as we document below, provinces do have a common time dynamics induced by overall economic growth. In other words (changing subscript notation slightly), ED appears to follow an AR(1) process with drift:

$$ED_{jt} = \mu_t + \rho ED_{jt-1} + \zeta_{jt} \tag{6}$$

where it is assumed that $E(\zeta_{jt}\zeta_{ks}) = 0$ for all $\{j,k\}$ and $\{s,t\}$. For stayers (for whom $j(i,t) = j(i,t_L) = j$), we are regressing

$$Y_{it} = \alpha + \beta ED_{jt_L} + \gamma ED_{jt} + \varepsilon_{it}$$

and, given (6), ED_{jt_L} will naturally be correlated with ED_{jt}, implying that if $E(\varepsilon_{it}|ED_{jt}) \neq 0$ then also $E(\varepsilon_{it}|ED_{jt_L}) \neq 0$. For movers (for whom $j = j(i,t) \neq j(i,t_L) = k$), however, we will be regressing:

$$Y_{it} = \alpha + \beta ED_{kt_L} + \gamma ED_{jt} + \varepsilon_{it}$$

and ED_{kt_L} and ED_{jt} are correlated only because of aggregate effects (especially recent ones, as farther ones exert diminishing effect as long as $\rho < 1$). In other words,

$$E(\varepsilon_{it}|ED_{jt}, \mu_t, \mu_{t-1}, ...) \neq 0, \text{ but } E(\varepsilon_{it}|ED_{kt_L}, \mu_t, \mu_{t-1}, ...) = 0.$$

Controlling for year effects, therefore, breaks the correlation between current firm density and firm density at learning age in the equation for movers. Since our interest centers on the identification of β, this is enough to achieve identification and obtain unbiased estimates of β. Using movers, however, may introduce a selection bias. For example, movers may be more risk tolerant, and risk tolerance may also explain selection into entrepreneurship. For this reason, we use a Heckman probit selection model where we use local internal migration rates as an exclusion restriction (see below for details).

Finally, we need to discuss the role of variables that determine both ED at learning age and persistently affect the propensity to become an entrepreneur and entrepreneurial ability, even after one moves from the learning age location. The presence of these variables represents threats to identification even in the sample of movers.

For example, differences in genetic endowments,[11] in culture, or in the quality of the school system might both determine heterogeneity across locations in ED at learning age and individual entrepreneurial outcomes later in life. Following Max Weber's culture theory, in certain areas entrepreneurship might be regarded as a particularly appealing occupational choice, and entrepreneurial success as a highly regarded outcome. Because culture is persistent, an individual who grows up in a high ED area might be both more likely to become an entrepreneur and exert more effort in entrepreneurship as a reflection of the culture of the place where she grew up. This story would give rise to the same type of correlation implied by the learning story and, because culture is portable, would also affect the specification where we fous on movers. A similar reasoning applies to genetic differences across people belonging to different communities.

To address these threats to identification in our movers sample, we use the argument that learning entrepreneurial abilities from entrepreneurial density presumably evolves at different frequencies and geographical reach than culture and genetics. In fact, we will show that ED changes substantially over the sample period even after netting out aggregate time effects, giving rise to non-trivial within-location time series variation. Culture (Williamson, 2000) and genetics (Cavalli Sforza and Bodmer, 1971) are instead processes that are likely to move at very low frequencies. Furthermore, while learning is clearly very local, culture and genetics usually span broader geographical areas. Hence, they can be accounted for by broader geographical controls than those that define variation in entrepreneurial density. Stated differently, if fixed local attributes are important, then $E\left(\varepsilon_{it}|ED_{jt_L}\right) \neq 0$, while $E\left(\varepsilon_{it}|ED_{jt_L}, Geo_s\right) = 0$, where Geo_s are detailed geographical dummies both for the current and the learning age location. Therefore, by comparing our estimates as we vary the number of spatial dummies (making them finer), we are able to assess the likelihood that fixed local attributes represent a credible threat to identification.

The other potential confounding factor is heterogeneous school quality. If a given geographical area is endowed with better schools, and school quality is a determinant of entrepreneurship, it will produce more and better entrepreneurs. Moreover, the effect will be long lasting, as schooling gets embedded in the human capital which travels with the individuals upon moving. We address this concern directly by documenting that there is

[11] A recent literature documents genetic influences in occupational choices at the individual level. Using adopted children, Lindquist, Sol, and Van Praag (2015) find that biological parents' occupational choices are correlated with those of their children, although the influence of adoptive parents is twice as large. Twin studies also conclude that a significant variation in entrepreneurship is explained by genes (Nicolaou et al., 2008; Zhang et al., 2009). This literature focusses on heterogeneity across individuals within a population. This may be very different from systematic differences in entrepreneurship across populations according to genetic distance.

no correlation between school quality and entrepreneurial density.

5 Data

5.1 The SHIW Sample

We use two main complementary data sources. The first is the Bank of Italy Survey of Households Income and Wealth (SHIW) which collects information on demographics, income and assets for a representative sample of Italian households. Starting in 1991, the survey is run biannually (with the exception of 1997) and we use all the 11 waves from 1991 to 2012 for a total of 62,990 observations. For our purposes, the SHIW contains data on occupations and earnings from various sources - including earnings from business. Moreover, for each individual it reports the province of birth and province of residence. The province is our geographical reference for measuring learning opportunities. Provinces are administrative units comparable in size to a US county. There are 95 of them at the start of the sample period.[12] To identify entrepreneurs we use two measures. The first is a broad measure that includes people who are self employed, partners of a company and owners that run an incorporated business (19% in total). The second is a narrow definition which only includes the latter category (8% of the sample); it replicates the entrepreneur definition in the ANIA survey described next. This sample allows us to study occupational choice but has limited information about the firm. Table 1, panel A shows summary statistics for the SHIW sample. The variables are defined in the appendix.

5.2 The ANIA Sample

Our second data source consists of detailed information on a sample of entrepreneurs and their firms. The data set is based on a survey conducted by ANIA (the Italian National Association of Insurance Companies), covering 2,295 private Italian firms employing between 10 and 250 employees. The survey was conducted between October 2008 and June 2009. It consisted of two distinct questionnaires. The first collected general information on the firm and was filled out by the firm officials on a paper form. The focus of this first questionnaire was on the type of firm-related insurance contracts that the firm had or was considering. The questionnaire also collected more general information on the firm (such as ownership structure, size and current performance) and its demographic characteristics. The second questionnaire collected information on the person in charge of running the firm.

[12] Over the sample period new provinces were created by splitoff of existing provinces; we use the initial 95 province classification.

The questionnaire was completed in face-to-face CAPI interviews by a professional interviewer. Several categories of data were collected, including information on personal traits and preferences, individual or family wealth holdings, family background, and demographics. The latter in particular includes information on the municipality where the individual (as well as his/her spouse) was born and where he/she was living at 18.

For approximately half of the firms, those incorporated as limited liability companies, we also have access to balance sheets. These data were provided by the CERVED Group, a business information agency operating in Italy. The data from the two sources were matched using a uniquely identifying ID number. This is the sample that we use in this paper. The data necessary to compute TFP are available for the years 2005-2007. We end up with 966 firms and almost 2,600 firm-year observations. TFP is computed using factor shares, assuming constant returns to scale (results are robust to alternative computation methods). Differently from the SHIW sample, we know the municipality in which the business is located. As our preferred geographical unit we use the *local labor systems* (LLS), i.e., territorial groupings of municipalities characterized by a certain degree of working-day commuting by the resident population, which represent self-contained labor markets and are therefore the ideal geographical unit within which to study local externalities. LLS are similar to the US MSA. We use the definition based on the 2001 Census, which identifies 686 LLS. Results are robust when performing the analysis at the provincial level.

Summary statistics for this sample are shown in Table 1, Panel B. The comparison with the SHIW sample indicates that they are fairly similar. The main differences are that the ANIA entrepreneurs are on average more educated, are less likely to have grown up or be resident in the South, and manage larger firms, due to the fact that the ANIA sampling scheme excludes firms with less than 10 employees and only includes limited liability firms. The appendix describes the survey design of the SHIW and ANIA surveys in greater detail and provides a precise description of the variables used in this study.

5.3 Measuring learning opportunities and other controls

We measure learning opportunities with firm density at "learning age". As explained above, as a reference measure of location, we use provinces for the SHIW sample and LLS for the ANIA sample.[13] To measure firm density we obtain census data on both the population and the number of firms[14] active in each location and year since 1951 and divide it by the

[13]This is due to data restrictions, as the province is the SHIW's lowest available level of geographical disaggregation.

[14]In the choice of the firm definition we are constrained by data availability in the early censuses. In particular, they only report data for production units, which are similar to a plant. Moreover, they do not

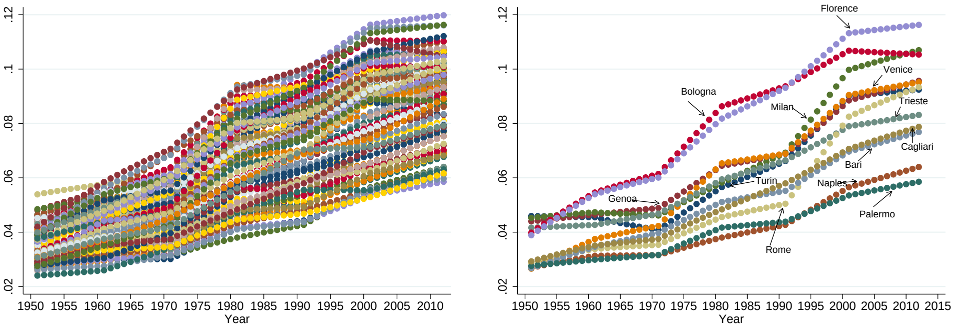
corresponding resident population. We then attach to each individual in our sample (either in the SHIW or the ANIA survey) the firm density in the location at learning age. Because the Census data are available for 1951, 1961, 1971, 1981, 1991 and 2011, we perform a simple linear interpolation at the province or LLS level for the mid-census years.

In the ANIA sample we know where each entrepreneur was living at learning age and can attach ED in the location where she was at that age. In the SHIW we know where the individual was born but not where she grew up; in these cases we assume that they grew up in the province of birth. This implies that in this sample our measure of learning opportunities contains some measurement error. This measurement error however is likely to be small. From the ANIA sample (where we observe both the place of birth and the place at learning age) we calculate that only 15% of people grew up in a province different from that of birth.

Our identification exploits both cross-sectional and time-series variation in firm density at learning age. Figure 1, Panel A shows the pattern of firm density over time for each province in the sample, while Panel B focuses on the largest Italian provinces. Density differs considerably both across provinces at each point in time as well as over time within provinces with very different time profiles. Consider individuals living in a given province X. They differ along two dimensions: their current age and the province where they grew up. Some grew up in the same province where they currently live, while others moved after spending their formative years in a different province. We can identify the effect of learning opportunities through two thought experiments. Everything else equal, we can compare the occupational decision and the performance as entrepreneurs of individuals currently located in province X who grew up in X in different times and hence faced different firm densities at learning age (i.e., individuals who grew up in Florence in the early 1950s versus early 1990s). Or we can compare the outcomes of individuals of the same age who grew up in different provinces, and hence faced different firm densities at learning age, before both moving to province X (e.g., individuals who are currently in Florence but grew up in different provinces, say Milan or Palermo). Because firm density is persistent, current density and density at learning age for individuals based in the province where they grew up tend to be relatively highly correlated (correlation coefficient 0.6), especially for younger individuals. Identification is facilitated by movers. For this subsample of individuals (22% in the SHIW and 26% in the ANIA sample) correlation between current density and density at learning age is much lower (0.2).

distinguish between business units and other types, such as government units. We therefore keep all units throughout. In the most recent censuses, non-business units account for less than 3% the of observations.

Figure 1: The evolution of firm density across Italian provinces, 1951-2009



(a) All provinces (b) Largest provinces

Source: Istat Census data

Finally, we complement our datasets with the number of bank branches per capita in each location-year as a measure of local credit market development.

6 Results

The two datasets we use have both advantages and disadvantages. The SHIW sample is representative of the Italian population, and as such is ideal to study the decision to become an entrepreneur. The ANIA survey instead only samples entrepreneurs. On the other hand, the SHIW only reports the current place of residence and the residence at birth, while ANIA also contains the location around age 18. Moreover, because the ANIA data are relative to firms, it allows us to construct the direct empirical counterpart of the Lucas model's measure of entrepreneurial ability, i.e., TFP. We begin to study occupational choice and entrepreneur's performance, measured by business income, in the SHIW sample. We then move on to the ANIA sample to dig deeper into the determinants of entrepreneurial performance.

6.1 SHIW sample: occupational choice

We start by estimating a probit model for the binary decision to become an entrepreneur. In our specifications, besides including firm density in the province where the individual was located at learning age, $ED_{j(i,t_L)t_L}$(here assumed to be the same as the province of birth), we control for firm density in the province of current residence, $ED_{j(i,t)t}$. We capture general geographical features that may affect occupational decisions (such as the cost of starting a business) by inserting dummies for the area of birth and for the current area of residence of the individual (either four macro area dummies - North-east, North-west, Center, South-islands- or 20 regional dummies). In addition, we control for individual demographics such as gender, age, educational attainment, work experience, a dummy if the parents were entrepreneurs and family characteristics (whether married, number of earners, and family size). A key issue in the choice to become an entrepreneur is access to finance. A large literature argues that liquidity constraints and easiness in raising external capital foster entrepreneurship (see e.g., Evans and Jovanovic, 1989; Banerjee and Newman, 1994). It might be that firm density at learning age reflects local financial development as more firms may be started where capital is easier to raise. To account for this we control for the number of bank branches per capita in the province at learning age and for the same variable in the province of residence at the time the survey was run. As shown by Guiso, Sapienza, and Zingales (2004) the number of bank branches per capita predicts the easiness in obtaining external finance. All regressions contain (unreported) dummies for education, year, and sector. Given that our main variable of interest (ED at learning age) varies at the province-year level, we cluster standard errors accordingly. Results are robust to alternative clustering schemes.

Results are shown in Table 2 for the broader definition of entrepreneurship, which includes the self employed, partners of a company and owners that run an incorporated business. Marginal effects are reported throughout. In column (1) we report the result of a regression with ED at learning age without controlling for current ED. People who grew up in provinces with a higher firm density are more likely to become entrepreneurs. As for the other controls, bank branches per capita at learning age have no statistically significant effect. Males are more likely to be entrepreneurs, as well as older and married individuals. Having a parent that was an entrepreneur has a strong positive impact of being an entrepreneur, consistent with most literature on the determinants of entrepreneurship. Moreover, the number of income recipients within a household also exerts a positive effect, arguably because employed family members are at time a source of startup capital and of income insurance, important to smooth out entrepreneurial income fluctuations.

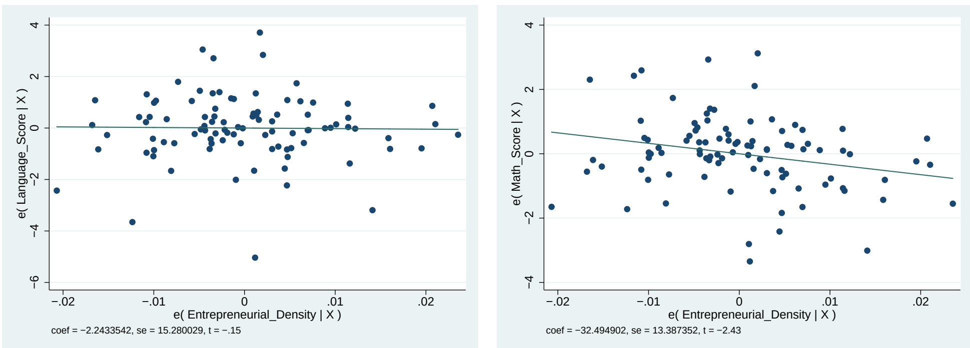
In column (2) we add current ED. This is a key control, given that, for stayers, current and learning age ED are correlated, so that the latter might just be proxying for the former. We also control for current bank branches per capita. As expected the coefficient on learning age ED decreases, from 1.14 to 0.75, but remains large and statistically significant. Current ED has a slightly larger coefficient (1.0) and is also significant.[15] Increasing ED at learning

[15] It is worth stressing that while the correlation between the choice to become an entrepreneur and current ED may suffer from the reflection problem (Manski, 1994), our variable of interest - ED at learning age - is

age by one standard deviation increases the probability that an individual decides to become an entrepreneur by 1.5 percentage points, 8% of the sample mean.

Having established this basic pattern, we now check whether it is robust to a number of potential objections. As discussed in Section 4, there is still the possibility that our results are driven by unobserved local factors that drive both ED at learning age and entrepreneurial outcomes later in life, such as school quality, genetic differences and differences in culture. Regarding school quality, ideally one would like to control for it at the local level at the time of learning. Unfortunately there is no source of information on school quality at the local level over the required time span and thus we cannot control for this potential confounding factor in the regressions. However, we do observe school quality in recent years. If, as the objection holds, school quality is higher in high ED areas and this leads to higher human capital (and thus better entrepreneurs), we should find a positive correlation between school quality and ED even today (when we have standardized measures of students achievements). We use test scores in fifth grade and run a regression of average test results at the province level on current ED, after controlling for macro area dummies. Figure 2 reports the regression line for test scores in language and math. We find no correlation for language scores and a slightly negative correlation for math scores. This evidence goes against the objection that our measure of ED may be proxying for unobserved school quality.

Figure 2: School test scores and entrepreneurial density, Italian provinces



(a) Language score

(b) Math score

The figure reports the regression line of test scores on ED at the province level, controlling for macro-area dummies. Source: Invalsi test scores and Istat data

To address the other potential sources of unobserved heterogeneity - genetic and cultural

immune from it.

differences across areas - we increase the number of spatial controls, reducing the contribution of the cross-sectional variability in the data to identify the parameters and thus exploit mostly the time series variation. The assumption is that such alternative determinants tend to move at much lower frequencies than ED (and learning entrepreneurial ability from it). Moreover, as argued above, learning is likely to be more localized than both culture and genetics, whose effect should be accounted for by finer geographical dummies. Both arguments imply that the coefficient of ED should become smaller as we increase the number of spatial controls if ED is mostly capturing cross sectional differences in genetic or cultural endowments but remain roughly unchanged if ED at learning age captures the possibility to accumulate entrepreneurial ability. In column (3) we introduce 20 regional dummies, both for the current location and for the area of learning location.[16] Results for the ED at learning age variable are unaffected, suggesting that fixed unobserved local characteristics are unlikely to be driving our estimates.

Finally, in the last column we focus on the sample of movers, i.e., individuals who were born in a province different from their current province of residence. This comparison allows to break the collinearity between current and learning age density. To control for selection into moving, we run a Heckman sample selection model. The exclusion restrictions (explaining gegraphical mobility but not the decision to become an entrepreneur) are indicators of local out-migration rates at learning age. The rank condition is satisfied: we find that local migration rates affects the individual probability of moving. Conditional on being a mover, we see no obvious reason why the migration rate should affect the probability to become an entrepreneur – even more so given the large set of controls we include in all the regressions.

To construct the exclusion restrictions, we use historical data on internal migration flows from the National Institute of Statistics. Given that our geographical unit is the province, ideally we would like to have data on out-of-province migration. Unfortunately, the data contains (for each region and year) only information on the number of individuals who move out of the region (a larger administrative unit than the province, roughly equivalent to a US state) and the (aggregate) number of individuals moving out of a municipality (a smaller administrative unit than the province, roughly equivalent to a US city).[17] The latter is a

[16] Regions are territorial units comprised on average by five provinces. We have also experimented with province dummies, which completely eliminate the cross sectional differences. The point estimates are similar but we loose statistical precision.

[17] Mobility out of the region is only available starting in 1995. To compute mobility out of the region before 1995 we take the average of the ratio between the number of movers out of the region and out of the municipality for the overlapping years. This gives the average share of movers out of the region on total movers. We then multiply mobility out of the municipality by this ratio to obtain an estimate of mobility out of the region for the years before 1995.

combination of intra- and inter-regional mobility. Since provinces are closer to a region than a municipality (there are 20 regions, 95 provinces, and 8,100 municipalities in Italy), we focus on out-of-region migration rates, which we obtain by dividing the annual number of out of the region migrants and the regional population. Given that we do not know the exact year of the move (as we only know province of birth and the current province of residence), we take the average mobility rate in the ten years before and ten years after learning age and include them in the first stage of the Heckman procedure. We report the first stage in the appendix. The mobility indicators are statistically significant. Since migration occurs in waves, we find the intuitive result that the likelihood to move is higher if past migration out of the region has been low or future mobility is higher. The results of the second stage are reported in Column (4). The basic result is unchanged but the coefficient becomes substantially larger, a pattern that will also emerge in the other regressions focusing on movers.

Table 3 replicates the same regressions using the more stringent definition of entrepreneurship which excludes self employment. This decreases the incidence of entrepreneurship from 19% to 8% (see Table 1). Results are qualitatively confirmed using this alternative definition. The point estimates are reduced by half (with the exception of the movers sample), which is expected as the share of entrepreneurs is substantially smaller. According to the estimates of column (2), increasing density at learning age by one standard deviation increases the probability that an individual becomes an entrepreneur by 0.8 percentage points, which represents a slightly larger increase relative to the sample mean than in the case of definition I (10% versus 8%).

6.2 SHIW sample: performance

We next study entrepreneurs' success, measured by income from business. Since this is available only for entrepreneurs, we estimate a Heckman selection model to correct for selection into entrepreneurship and use as an exclusion restriction the number of family earners, which we assume affects the decision to become an entrepreneur (if other family earners offer some earnings risk diversification) but not entrepreneurial success. Otherwise the set of controls is the same as in the probit estimates in Tables 2 and 3. Results are shown in Table 8 for the broad definition of entrepreneur. ED at learning age has a positive and strongly significant effect on the (log of) entrepreneur's earnings. The effect is slightly smaller but retains fully its statistical significance even after controlling for the current firms density in the province (column 2). The effect of current ED is positive and significant, consistent with a large literature on agglomeration economies (Rosenthal and Strange, 2004a; Moretti, 2011), but the effect of ED at learning age is almost twice as large (5.4 vs. 3.2), and highly statistically significant. In terms of magnitude, the estimate implies that increasing density at learning age by one standard deviation increases entrepreneurial income by 11%.

According to these estimates, external effects related to firm density that take place at learning age are more important for firm profits than current externalities. This is an important result for the literature on agglomeration economies and the channels through which they operate. Duranton and Puga (2004b) propose three channels through which agglomeration economies can affect firm performance: the opportunities to learn from other firms, the size of the local work force (which can increase the division of labor and the quality of job-worker matches), and a greater variety of intermediate inputs. Of these three channels, only learning can have effects that persist once an entrepreneur moves from a high density area. Our results therefore indicate that learning externalities are at play in the determination of agglomeration economies.[18] Moreover, they also point to a specific channel of learning externalities, that is, those that get embedded in the individual's human capital in the coming of age years, which are distinct from contemporaneous knowledge spillovers that result from being located in a certain area in the current period.

As for the effect of other controls, we find that male entrepreneurs earn a substantial premium (more than 40%) over female entrepreneurs. Older entrepreneurs earn more, as well as those with a parent that was already an entrepreneur[19] and who are married.

In column (3) we include regional dummies (both for current and learning age location) and find no differences in the estimates, in line with the hypothesis that the ED at learning age is not proxying for other unobservables that determine both ED at learning age and entrepreneurial success today.

In the last column we focus on the sample of movers, where identification is robust to the concerns discussed in Section 4. Column (4) corrects for joint selection into entrepreneurship as well as moving, where the instruments for mobility are the same as in the occupational choice regressions of the previous tables. We find that the basic conclusions are confirmed, with the effect becoming slightly larger compared to the whole sample.

[18] Of course, this does not imply that the other sources of externalities are absent. In fact, ED is a natural indicator of learning externalities, but not necessarily of the size of the local workforce or of intermediate input varieties, typically captured by other indicators (Glaeser et al., 1992).

[19] Growing up in an entrepreneurial family can be an important alternative source of learning. Of course, this cannot be told apart from genetic effects, so that one cannot interpret this coefficient planing as evidence for learning.

Table 5 replicates the estimate using the stricter definition of entrepreneurship. This reduces the observations from 11,498 to 5,083. The reduction in the sample size reduces the statistical power so that, in the specification with regional dummies, we loose significance. However, the pattern that emerges is fully consistent with that based on the broader definition of entrepreneurship. We also find that in the movers sample the coefficient is substantially larger than in the overall sample, arguably because breaking the correlation between ED at learning age and current ED is more important in the smaller sample of strictly defined entrepreneurs.

6.3 ANIA sample: performance

To further investigate the effects of ED on entrepreneurial quality, we now turn to the ANIA sample. We use the same framework as in the SHIW sample, with a few exceptions. First, we only study entrepreneurial success, as this is a sample of entrepreneurs and therefore cannot be used to study occupational choice. Following Lucas (1978), we measure entrepreneurial quality with firm TFP. Second, we measure ED in the location in which the entrepreneur was actually living at age 18, rather than at birth. This is indeed important, as the two locations differ for about 15% of cases in our sample. Third, the set of controls is the same as in the SHIW regressions, with the exception that experience is defined in terms of years since the individual started managing the firm, an information not avaliable in the SHIW and that could have an independent effect of performance. As before, we cluster standard errors at learning age-LSS level and, as before, results are robust to alternative clustering schemes.

Table 6 shows the results. ED at learning age has a positive and precisely estimated effect on the firm TFP (column 1). Increasing ED at learning age by one standard deviation (0.02) increases TFP by 8.6%. None of the other controls display a significant effect, arguably due to the fact that we have a much smaller sample compared to the SHIW one. It is theorefore remarkable that ED at learning age is statistically significant also in this dataset. In column (2) we add current ED, finding a positive but statistically insignificant estimate. The coefficient on ED at learning age increases slightly (to about 5) and remains statistically significant at the 5% level. As in the SHIW data, therefore, we find the striking result that learning age externalities play a stronger role than current production externalities. We also notice that the elasticity of entrepreneurial quality to ED is very close in the two datasets, although the sample and the variables used to measure entrepreneurial quality are different.

The remaining columns perform a series of robustness checks. First, we control for ED at birth (column 3). A growing literature stresses the role of *early* education on professional outcomes (Heckman, Pinto, and Savelyev, 2013). Extrapolating from this literature it may be argued that the economic environment that matters most to accumulate entrepreneurial ability is the one in the early years of development. In the ANIA sample we have direct information on place of residence both at birth and at 18. For movers, this breaks the strong correlation in ED at birth and at learning age that results from assuming that the two locations are the same, as we are forced to do in the SHIW sample. The estimated coefficient of ED at birth is not statistically different from zero, while that of ED at learning age is unaffected, supporting the idea that learning entrepreneurial talents from other entrepreneurs occurs in the early years or just before the beginning of one's professional life. This result also allows us to address a potential competing explanation: genetic differences. In fact, the birthplace should be a better identifier of genetic influences than the place where one grows up. The significance of ED at learning age and the lack of significance of ED at birth allow us to reject the hypothesis that higher entrepreneurial density proxies for genetic propensity to engage in entrepreneurship.

These findings could still be consistent with a cultural explanation if the culture that matters for entrepreneurship is not acquired in the early years of life but only later. If the density where one grows up is a reflection of an underlying entrepreneurial culture, our measure might just be proxying for it rather than for learning opportunities. To address this, we rely on the idea that culture evolves slowly and the geographical unit that is covered by a culture is broader than that where learning entrepreneurial abilities from firms takes place. Accordingly, in column (4) we expand the number of spatial controls to account for potential spatially correlated effects. Given that the geographical unit for ED is the LLS, we can use finer controls than those of the SHIW sample and insert 95 province dummies (rather than 20 regional dummies). Since provincial governments are in charge of managing schools, provincial dummies also account for any persistent geographical differences in the quality of schooling. As before, we use separate dummies for location at learning age and current location. Again, we find that the point estimates are unchanged – if anything, they become larger – and that the coefficient is statistically significant at the 5% level.[20]

Finally, we focus on the the sample of movers employing a Heckman sample selection

[20]We have also experimented with dummies at the LLS level, thus exploiting for identification of learning effects only on the time variation in ED. As with the SHIW data, estimates for the effect of ED at learning age are similar in magnitude but with larger standard errors. This is not surprising, given the large number of dummies (more than 400) and the limited sample size.

model. Compared to the SHIW regressions, we introduce two slight modifications given that we have richer data. First, we use the mobility rate out of the municipality rather than out the region. In fact, a LLS contains on average 10 municipalities while regions contain on average around 40 LLS. Mobility out of the municipality is therefore a closer proxy to mobility out of the LLS than mobility out of the region. Second, we only use the average mobility rate in the 10 years after learning age. Differently from the SHIW sample (where we observe the province of birth but not the province of residence at learning age), in the ANIA data we know that the individual was still resident in the LLS of learning at 18, so we can disregard prior mobility. The first stage, reported in the appendix, shows that the instrument has the expected positive sign and is statistically significant. Column (5) shows that, as in the SHIW sample, the effect of ED at learning age becomes stronger and more precisely estimated.

As a final check, we have used sales per worker to measure entrepreneurial quality. While TFP is the closest empirical counterpart to ability in the Lucas model, estimating TFP requires more assumptions than just computing a simple measure of labor productivity. Results in Table 7 confirm all those obtained with TFP. The coefficient on ED at learning age tends to be larger and more precisely estimated. Increasing density at learning age by one standard deviation results in an increase in sales per worker of around 22%. A possible explanation is that growing up in denser areas not only improves ability, but it also leads entrepreneurs to increase the capital-labor and intermediate inputs-labor ratio, leading to an even stronger effect on labor productivity.

Overall, we take this evidence as supportive of the idea that one important channel through which individuals acquire entrepreneurial abilities is early exposure to a richer entrepreneurial environment.

7 What features of entrepreneurship are learnable?

Being an entrepreneur requires multiple talents. The entrepreneur develops new ideas, evaluates their market appeal, organizes production, bears the risk of failure. Sorensen and Chang (2008) argue that entrepreneurship is defined by three features: risk bearing, propensity to innovate, and coordination ability. These three features are well rooted in the economics tradition. The role of the entrepreneur as the bearer of risk dates back to Knight (1921), who ascribes the very existence of the firm to its role as an insurance provider. Schumpeter (1911) emphasized the role of the entrepreneur as the carrier of innovation and creative destruction deriving from innovation as the key source of growth in market economies. But in addition to a propensity to innovate and to bear the risk of such a process, the entrepreneur also needs to be able to implement an idea, organize production, and bring the product to the market. Marshall (1890) was the first to stress the importance of localized spillovers to learn "the mysteries of the trade".

In this section we offer empirical evidence on how "learnable" these three features are, using information from the ANIA survey. In the face-to-face interview respondents were asked a set of questions aimed at eliciting risk preferences and identifying personality traits. We briefly describe them here and report the full questions in the Appendix. First, respondents were asked to choose between different investment strategies with decreasing risk-returns profiles, ranked from 1 (high risk and high return) to 5 (low risk and low return). We use the answers to this question as a measure of risk aversion. Second, the respondent was asked to express, on a scale from 1 to 5, their preferences regarding drawing a ball from an urn with 50 green and 50 yellow balls vs. drawing it from an urn containing an unknown share of balls of each color. We use this question to measure ambiguity aversion. A measure of self-confidence was obtained by asking the entrepreneur whether she ranked herself below, at the same level or above the average ability or other entrepreneurs. Optimism is measured by the answer (on a scale from 0 to 10) to how much the respondent agrees with the statement "*All things considered I expect more good than bad things in life*". Job satisfaction was measured from the answer to the question: "*Excluding the monetary aspects and considering only the other characteristics of your job, can you tell me if they give you more satisfaction or annoyance?*", again on a scale 0-10. Summary statistics for these variables are reported in Table 8, Panel A.

The entrepreneur's propensity to innovate is measured by two (arguably imperfect) proxies. The first is the share of 2007 sales due to innovative or significantly improved products or services that were introduced in the market in the 2005-2007 period. The second is a score of the practices used by the firm to manage the innovation process, collected in the managerial practices follow up survey described below. Descriptive statistics for all these variables are in Table 8, Panel B.

The original survey lacks information on the ability to coordinate production or manage the firm. In the Fall of 2012 we re-contacted the entrepreneurs in the ANIA sample and asked them to participate in a second round of interviews to assess their managerial practices. We used the methodology developed by the World Management Survey (WMS, see Bloom and Van Reenen (2010a,b)). The WMS is based on a telephone double-blind survey technique and comprises a set of open-ended questions, whose qualitative answers are then recoded into quantitative measures with a score ranging between 1 (worst) to 5 (best managerial practices). The questionnaire comprises five sections that consider different key areas of management practices. We investigate three areas. The first section is *Monitoring* and focuses on the monitoring of performance and reviewing the results. The second section is *Targets* and aims at assessing the respondents' managerial ability to identify quantitative and qualitative targets, their interconnection and their temporal cascade. The third section is *People* and it is concerned with human resource management, ranging from promoting and rewarding employees based on performance, removing poor performers, and hiring and retaining the best workers. The average score of the three areas defines the index of overall managerial ability.[21] Of the original 966 entrepreneurs, we were able to re-interview 388 (details on the data collection methodology are in the appendix, section A.2). Descriptive statistics are in Table 8, Panel C.

As a first check, in Appendix Table A.3 we regress TFP on personality traits. We have no a priori on how the degree of risk aversion or optimism should correlate with firm level TFP. Indeed, the correlation is always insignificant. Next, we check if these traits are correlated with ED at learning age. Given that what we are trying to measure is more elusive than occupational choice or performance, and that the number of observations is smaller, as we only use the cross section rather than the three years of data as with TFP, for all regressions in this section we start with a parsimonious specification which only includes macro area and sector dummies, and then add the individual controls. The results are reported in Table 9. In general, we find no evidence that entrepreneurial traits are affected by ED at learning age. Growing up in areas with greater firm density seems to lead to higher risk aversion in the specification with individual controls (column 2), but precision is low and the estimate changes sign and is not statistically significant controlling only for sector and area dummies (column 1). Moreover, one would expect that ED at learning age reduces risk aversion, as risk tolerance is one of the key features of entrepreneurship. This evidence instead is consistent with the predominant role of the innate component in explaining individual risk preferences found by Cesarini et al. (2009) using twin studies. All other traits appear uncorrelated with ED at learning age. Overall, these results suggests that traits are not affected by the entrepreneurial context at learning age, arguably because a large component is genetically determined or acquired much earlier, perhaps within the

[21]The original WMS contains two additional areas, operations and leadership. These areas investigate practices that are very sector specific, such as the operation of the production unit. Given that we have firms from both manufacturing and services, we only investigated areas where practices are sufficiently similar to allow for the use of the same scheme of interview. In any case, in all regressions we use sector dummies.

family or at school (Heckman, Pinto, and Savelyev, 2013).

Next, we run the same exercise for innovation capacity. Table A.3 (column 6) and A.4 (column 5) in the Appendix show that the two measures of innovation are not correlated with TFP. Consistently, we find no effect of *ED* at learning age on innovation capacity (Table 10): the Schumpeterian component of entrepreneurship appears unrelated to *ED* at learning age. This is indeed in line with Schumpeter's original notion of the innovator as the one that challenges established knowledge with new, unforeseen ideas – something that is unlikely to be learned from others.

The ability to manage, however, is more likely to be learnable. Indeed, managerial skills are precisely what one learns in business schools and colleges specialized in teaching entrepreneurship. But these skills may possibly be learned also before college by direct observation and exposure to adopted practices by the firms in the place where one grows up.

We test this potential channel using the measures of managerial practices discussed above. To first validate these measures, in Table A.4 we report the results of regressions in which productivity and firm size (measured by the log of the number of employees) are regressed on the managerial practices scores. As shown by Bloom and Van Reenen (2007) and Bloom, Sadun, and Van Reenen (2012), managerial practices are strongly correlated with the size of the firm and its productivity. This holds in our sample too: each type of managerial practice, as well as the general index, is positively and significantly correlated with TFP and firm size. Table 11 runs regressions of these measures on *ED* at learning age controlling for current density. Interestingly, in the parsimonious specifications in which we control only for current density and area and sector dummies, density at learning age has a positive and statistically significant correlation with managerial practices, while current density has a small and insignificant effect (columns 1, 3, and 5). The exception is *People*, where the *ED* at learning age coefficient has a p-value of 11 percent. When we introduce the individual controls, the effect of density at learning age retains its positive effect but its size halves on average and the estimate looses precision, so that none of the coefficient is statistically significant. This is most likely a reflection of the fact that measuring managerial practices is a difficult task and that we have a limited number of observations (less than 400), reducing statistical power. It turns out that the loss of significance of *ED* learn in Table 11 is due to the inclusion of the age and experience variables. These variables are mechanically correlated with *ED* at learning age, since the latter has a time varying component that trends similarly to age and experience. The limited statistical power prevents us from identifying separately the two effects.

There is also another, more economic reason that might explain the difficulty in singling out the aspects of entrepreneurship that can be learned. Lazear (2005) argues that an entrepreneur is a "Jack-of-all-trades", i.e., an individual with a balanced set of skills, rather than one that excels in any particular activity. Using data on Stanford GSB MBAs, he finds that those who tend to perform uniformly well in (but not necessarily at the top of) all courses are indeed more likely to become entrepreneurs than those who excel in specific subjects. Similar conclusions are reached by Bruhn, Karlan, and Schoar (2013) in their randomized trial in which managerial consulting services are provided to 150 SMEs in Mexico. They find that managerial consulting does improve overall firm performance, but no single aspect of managerial practices emerges as a key for the improvement. Profits and TFP are comprehensive measures of entrepreneurial capability and clearly correlate with learning opportunities. Singling out specific aspects, such as traits or particular managerial capabilities, might instead be more difficult, as there is no single component that by itself can explain entrepreneurial ability. This confirms the elusive nature of what makes a good entrepreneur.

Overall, we take this evidence as suggesting that managerial capabilities can be learned from other entrepreneurs, while both traits and innovation capacity might be more innate components that are less subject to the influence of the economic environment.

8 Conclusions

This paper analyzes the extent to which growing up in a high entrepreneurial area increases both the likelihood that an individual becomes an entrepreneur and her entrepreneurial ability or success. We find evidence that this is indeed the case, as would be implied by models where entrepreneurial ability is socially acquired. Interestingly, the effects of entrepreneurial density at learning age are stronger than those of current entrepreneurial density, which captures more traditional spillover effects. A remarkable finding is that the results we find hold in two distinct datasets and are robust to a large set of controls. Moreover, we find suggestive evidence that individuals growing up in high firm density areas acquire managerial skills, but that individual traits reflecting risk aversion, aversion to ambiguity, self-confidence or optimism, and propensity to innovate (which are traditionally associated to entrepreneurship) are independent of location. This suggests that the "personality traits" factor of entrepreneurship has a larger innate component, swamping any effect played by the environment.

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Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Panel A: SHIW Sample					
Entrepreneur, Def. I	0.19	0.39	Mover-Entrepreneur	0.19	0.39
Entrepreneur, Def. II	0.08	0.28	Income (Log)	9.04	0.87
ED learn	0.05	0.02	Born NorthW	0.19	0.39
ED today	0.08	0.02	Born NorthE	0.21	0.40
Male	0.62	0.49	Born Center	0.20	0.40
Age	44.60	8.51	Born South	0.40	0.49
Experience	24.32	10.25	Resident NorthW	0.24	0.43
Parent Entr.	0.13	0.33	Resident NorthE	0.22	0.41
Elementary school	0.12	0.33	Resident Center	0.22	0.41
Junior HS	0.33	0.47	Resident South	0.32	0.47
HS degree	0.39	0.49	Agriculture	0.04	0.20
College	0.14	0.35	Manufacturing	0.23	0.42
Post graduate	0.01	0.08	Construction	0.07	0.25
Married	0.77	0.42	Services and others	0.66	0.47
Family size	3.38	1.18	Firm size	1.13	19.09
N. of income recipients	2.01	0.82	LC learn	0.20	0.11
Mover	0.22	0.42	LC Today	0.51	0.20
Panel B: ANIA Sample					
TFP (log)	2.45	0.90	Learn in Center	0.19	0.39
ED learn	0.06	0.019	Learn in South	0.22	0.41
ED today	0.08	0.015	Resident in NorthW	0.31	0.46
Male	0.67	0.46	Resident in NorthE	0.30	0.46
Age	47.04	10.47	Resident in Center	0.20	0.30
Years in control	15.84	11.00	Resident in South	0.19	0.40
Parent Entr.	0.36	0.48	Mining	0.03	0.17
Elementary school	0.01	0.08	Manufactuing	0.35	0.48
Junior HS	0.07	0.25	Utilities	0.01	0.09
HS degree	0.68	0.47	Construction	0.08	0.27
College	0.23	0.42	Trade	0.24	0.43
Post graduate	0.02	0.13	Transport	0.04	0.20
Married	0.78	0.41	Other services	0.24	0.43
Family size	3.06	1.17	Employees	34.30	40.38
Mover	0.26	0.44	LC learn	0.25	0.11
Learn in NorthW	0.30	0.46	LC Today	0.62	0.17
Learn in NorthE	0.29	0.45			

Note: See appendix A.3 for the definition of the variables.

Table 2: The probability of becoming an entrepreneur, SHIW sample, Definition I

	(1)	(2)	(3)	(4)
ED learn	1.139***	0.753**	0.659*	3.325***
	(0.280)	(0.319)	(0.370)	(1.233)
ED today		1.001***	2.021***	0.243
		(0.331)	(0.436)	(1.154)
LC learn	-0.005	-0.001	0.000	-0.014
	(0.008)	(0.009)	(0.011)	(0.021)
LC today		-0.023	-0.014	-0.140***
		(0.017)	(0.020)	(0.044)
Male	0.037***	0.037***	0.037***	0.059***
	(0.005)	(0.005)	(0.005)	(0.015)
Age	0.021	0.010	0.001	0.019
	(0.026)	(0.027)	(0.029)	(0.083)
Experience	0.002***	0.002***	0.002***	0.003*
	(0.000)	(0.000)	(0.000)	(0.002)
Parent Entr.	0.136***	0.136***	0.135***	0.099***
	(0.007)	(0.007)	(0.007)	(0.017)
Married	0.016***	0.016***	0.016***	0.005
	(0.006)	(0.006)	(0.006)	(0.020)
Family size	0.000	0.001	0.001	0.002
	(0.002)	(0.i002)	(0.002)	(0.007)
N. income	0.013***	0.012***	0.012***	0.019**
recepients	(0.003)	(0.003)	(0.003)	(0.008)
λ_{mover}				-0.681**
				(0.278)
Observations	62,990	62,990	62,990	13,360
Area dummies:				
Macro-area of birth	X	X		X
Macro-area of residence	X	X		X
Region of birth			X	
Region of residence			X	

Note: Probit regressions for occupational choice. The dependent variable is a dummy equal to one if the individual is an entrepreneur. Entrepreneur definition I includes: (a) Individual entrepreneurs, (b) Owner or member of family business, and (c) working shareholder/partner, (d) Self-employed/Craft workers. ED learn is entrepreneurial density at 18 in the place of birth, ED today is current entrepreneurial density in the place of residence. LC are liquidity constraints, defined as bank branches over resident population. All regressions include year, education and sector dummies. Column (4) only uses the sample of movers, correcting for selection with a Heckman model in which the excluded variables are the the average mobility rate out of the region of birth in the ten years before and after the learning age. Robust standard errors in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%.

Table 3: The probability of becoming an entrepreneur, SHIW sample, Definition II

	(1)	(2)	(3)	(4)
ED learn	0.791***	0.421*	0.312	4.766***
	(0.194)	(0.220)	(0.257)	(0.854)
ED today		0.768***	1.307***	-1.338
		(0.232)	(0.289)	(0.926)
LC learn	-0.008	-0.008	-0.006	-0.019
	(0.005)	(0.006)	(0.008)	(0.023)
LC today		-0.003	-0.006	-0.108**
		(0.012)	(0.013)	(0.046)
Male	0.007**	0.007**	0.007**	0.023*
	(0.003)	(0.003)	(0.003)	(0.012)
Age	0.047**	0.032*	0.025	0.105*
	(0.019)	(0.019)	(0.021)	(0.061)
Experience	0.001**	0.001**	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Parent Entr.	0.091***	0.091***	0.090***	0.093***
	(0.006)	(0.006)	(0.006)	(0.035)
Married	0.025***	0.025***	0.024***	0.010
	(0.004)	(0.004)	(0.004)	(0.025)
Family size	0.000	0.000	0.001	0.004
	(0.002)	(0.002)	(0.002)	(0.005)
N. income	0.019***	0.018***	0.018***	0.028**
recepients	(0.002)	(0.002)	(0.002)	(0.011)
λ_{mover}				-1.435**
				(0.472)
Observations	56,485	56,485	56,485	12,244
Area dummies:				
Macro-area of birth	X	X		X
Macro-area of residence	X	X		X
Region of birth			X	
Region of residence			X	

Note: Probit regressions for occupational choice. The dependent variable is a dummy equal to one if the individual is an entrepreneur. Entrepreneur definition II includes (a) Individual entrepreneurs, (b) Owner or member of family business, and (c) working shareholder/partner and excludes (d) Self-employed/Craft workers. ED learn is entrepreneurial density at 18 in the place of birth, ED today is current entrepreneurial density in the place of residence. LC are liquidity constraints, defined as bank branches over resident population. All regressions include year, education and sector dummies. Column (4) only uses the sample of movers, correcting for selection with a Heckman model in which the excluded variables are the the average mobility rate out of the region of birth in the ten years before and after the learning age. Robust standard errors in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%.

Table 4: Entrepreneurial income, SHIW sample, Definition I

	(1)	(2)	(3)	(4)
ED learn	6.794***	5.489***	5.520***	7.113**
	(1.123)	(1.295)	(1.459)	(2.879)
ED today		3.191**	3.774**	0.902
		(1.262)	(1.660)	(2.776)
LC learn	-0.128***	-0.115***	-0.131***	-0.085
	(0.030)	(0.033)	(0.044)	(0.064)
LC today		-0.065	-0.070	0.014
		(0.062)	(0.070)	(0.120)
Male	0.451***	0.453***	0.444***	0.430***
	(0.023)	(0.023)	(0.022)	(0.053)
Age	0.502***	0.460***	0.452***	0.489**
	(0.110)	(0.112)	(0.119)	(0.245)
Experience	-0.003	-0.003	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.005)
Parent Entr.	0.093***	0.093***	0.092***	0.123**
	(0.025)	(0.025)	(0.024)	(0.059)
Married	0.123***	0.124***	0.120***	0.066
	(0.026)	(0.026)	(0.026)	(0.058)
Family size	0.009	0.009	0.010	0.041**
	(0.009)	(0.009)	(0.009)	(0.017)
λ_{entr}	0.192***	0.190***	0.177***	0.225
	(0.028)	(0.028)	(0.027)	(0.140)
λ_{mover}				-0.072
				(0.069)
Observations	11,498	11,498	11,498	2,009
Area dummies:				
Macro-area of birth	X	X		X
Macro-area of residence	X	X		X
Region of birth			X	
Region of residence			X	

Note: The dependent variable is log income from entrepreneurial activity. Entrepreneur definition I includes: (a) Individual entrepreneurs, (b) Self-employed/Craft workers, (c) Owner or member of family business, and (d) working shareholder/partner. ED learn is entrepreneurial density at 18 in the place of birth, ED today is current entrepreneurial density in the place of residence. LC are liquidity constraints, defined as bank branches over resident population. All regressions include year, education and sector dummies. All regressions are the second stage of a Heckman two stage model to correct for the choice of becoming an entrepreneur. The excluded variable is the number of income recipients in the family. Column (4) only uses the sample of movers, correcting for selection with a Heckman model in which the excluded variables are the the average mobility out of the region of birth in the ten years before and after the learning age. Robust standard errors in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%.

Table 5: Entrepreneurial income, SHIW sample, Definition II

	(1)	(2)	(3)	(4)
ED learn	5.812***	3.982*	2.780	9.460**
	(1.820)	(2.095)	(2.389)	(4.720)
ED today		4.961**	8.438***	0.205
		(2.162)	(2.882)	(4.366)
LC learn	-0.092*	-0.069	-0.069	-0.105
	(0.049)	(0.056)	(0.070)	(0.118)
LC today		-0.120	-0.159	0.282*
		(0.098)	(0.117)	(0.168)
Male	0.408***	0.409***	0.399***	0.280***
	(0.035)	(0.035)	(0.034)	(0.079)
Age	0.631***	0.570***	0.526***	0.714*
	(0.176)	(0.182)	(0.196)	(0.417)
Experience	-0.002	-0.003	-0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.007)
Parent Entr.	0.202***	0.202***	0.203***	0.299***
	(0.047)	(0.047)	(0.046)	(0.115)
Married	0.063	0.065	0.060	-0.024
	(0.046)	(0.046)	(0.045)	(0.116)
Family size	0.008	0.008	0.007	0.108***
	(0.015)	(0.015)	(0.015)	(0.030)
λ_{entr}	0.413***	0.410***	0.393***	0.584**
	(0.051)	(0.051)	(0.050)	(0.227)
λ_{mover}				-0.020
				(0.106)
Observations	5,083	5,083	5,083	906
Area dummies:				
Macro-area of birth	X	X		X
Macro-area of residence	X	X		X
Region of birth			X	
Region of residence			X	

Note: The dependent variable is log income from entrepreneurial activity. Entrepreneur definition II includes (a) Individual entrepreneurs, (b) Owner or member of family business, and (c) working shareholder/partner and excludes (d) Self-employed/Craft workers. ED learn is entrepreneurial density at 18 in the place of birth, ED today is current entrepreneurial density in the place of residence. LC are liquidity constraints, defined as bank branches over resident population. All regressions include year, education and sector dummies. All regressions are the second stage of a Heckman two stage model to correct for the choice of becoming an entrepreneur. The excluded variable is the number of income recipients in the family. Column (5) only uses the sample of movers. Column (6) uses the sample of movers, correcting for selection with a Heckman model in which the excluded variable is a dummy equal to one if the entrepreneur is married and his/her spouse was born in a different province than his/hers. Robust standard errors in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%.

Table 6: TFP and ED at learning age, ANIA sample

	(1)	(2)	(3)	(4)	(5)
ED learn	4.304**	5.003**	5.939**	6.136**	9.974***
	(1.858)	(2.152)	(2.318)	(2.731)	(3.419)
ED today		3.019	3.179	2.312	2.943
		(2.515)	(2.550)	(4.517)	(4.442)
LC learn	-0.094	-0.019	-0.010	0.090	0.199
	(0.101)	(0.105)	(0.106)	(0.224)	(0.172)
LC Today		-0.371*	-0.386*	-1.261	-0.281
		(0.200)	(0.203)	(0.829)	(0.343)
Male	-0.068	-0.074	-0.071	-0.042	-0.036
	(0.048)	(0.048)	(0.049)	(0.052)	(0.099)
Age	0.216	0.311	0.282	0.433	0.847*
	(0.192)	(0.205)	(0.213)	(0.326)	(0.435)
Experience	0.001	0.002	0.002	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Parent Entr.	-0.068	-0.073	-0.077	-0.075	0.126
	(0.050)	(0.050)	(0.051)	(0.053)	(0.103)
Married	0.094	0.095	0.103	0.082	0.063
	(0.066)	(0.066)	(0.066)	(0.071)	(0.136)
Fam. Size	-0.004	-0.004	-0.009	-0.006	-0.005
	(0.022)	(0.022)	(0.023)	(0.024)	(0.043)
ED birth			-2.915		
			(3.215)		
λ_{mover}					0.152
					(0.293)
Observations	2,586	2,586	2,547	2,586	2,580
Area dummies:					
Macro-area of residence	X	X	X		X
Macro-area of birth	X	X	X		X
Province of residence				X	
Province of birth				X	

Note: The dependent variable is log TFP. All regressions are based on the data for the years 2005-2007 and include year, education and sector dummies. Column (5) only uses the sample of movers, correcting for selection with a Heckman model in which the excluded variable is the the average mobility rate out of the municipality where the individual was living at learning age in the ten years after the learning age. Standard errors clustered at the level of the LLS-year of learning. Significance levels: *: 10%, ** : 5%, *** : 1%.

Table 7: Sales per worker and ED at learning age, ANIA sample

	(1)	(2)	(3)	(4)	(5)
ED learn	11.292***	9.923***	8.263**	8.991**	16.007***
	(2.629)	(2.995)	(3.229)	(3.815)	(5.060)
ED today		1.913	1.468	5.748	-0.249
		(3.610)	(3.641)	(5.836)	(6.761)
LC learn	-0.182	-0.210	-0.215	-0.441	0.004
	(0.128)	(0.141)	(0.142)	(0.303)	(0.232)
LC Today		0.099	0.110	-0.869	-0.012
		(0.280)	(0.282)	(0.811)	(0.523)
Male	0.097	0.102	0.094	0.095	0.260*
	(0.068)	(0.068)	(0.069)	(0.070)	(0.140)
Age	0.255	0.151	0.202	-0.252	0.907
	(0.256)	(0.289)	(0.302)	(0.421)	(0.669)
Experience	0.005	0.005	0.005	0.007*	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
Parent Entr.	-0.059	-0.058	-0.057	-0.089	0.150
	(0.068)	(0.068)	(0.069)	(0.073)	(0.149)
Married	0.121	0.124	0.119	0.086	0.286
	(0.089)	(0.089)	(0.090)	(0.097)	(0.187)
Fam. Size	-0.007	-0.008	-0.004	-0.017	-0.031
	(0.032)	(0.032)	(0.032)	(0.034)	(0.054)
ED birth			5.089		
			(4.334)		
λ_{mover}					0.323
					(0.540)
Observations	2,679	2,679	2,637	2,679	2,673
Area dummies:					
Macro-area of residence	X	X	X		X
Macro-area of birth	X	X	X		X
Province of residence				X	
Province of birth				X	

Note: The dependent variable is log of sales per worker. All regressions are based on the data for the years 2005-2007 and include year, education and sector dummies. Column (5) only uses the sample of movers, correcting for selection with a Heckman model in which the excluded variable is the the average mobility rate out of the municipality where the individual was living at learning age in the ten years after the learning age. Standard errors clustered at the level of the firm. Significance levels: *: 10%, ** : 5%, *** : 1%.

Table 8: Descriptive statistics, traits, managerial practices and innovation

Variable	Obs	Mean	Std. Dev.	Min	Max
	Panel A: Traits				
Risk aversion	966	2.70	.67	1	4
Ambiguity aversion	954	3.40	1.44	1	5
Confidence	944	2.18	.40	1	3
Optimism	946	7.33	1.76	0	10
Satisfaction	935	7.47	1.67	0	10
	Panel B: Innovation				
Share innov.	736	17.43	24.46	0	100
Innov. practices	388	2.09	1.2	1	5
	Panel C: Managerial practices				
Management	388	2.41	.66	1	4.41
Monitoring	388	2.67	.82	1	5
Targets	388	2.41	.90	1	5
People	388	2.33	.64	1	5

Note: See appendix A.3 for the definition of the variables.

Table 9: Entrepreneurial traits and ED at learning age, ANIA sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Risk aversion		Ambiguity aversion		Confidence		Optimism		Satisfaction	
ED learn	-0.842	3.832*	-4.822	-0.881	-0.950	0.168	2.570	-1.562	3.025	5.731
	(1.401)	(2.118)	(2.969)	(4.609)	(0.819)	(1.244)	(4.042)	(6.211)	(3.816)	(5.537)
ED today	1.160	-1.729	-4.167	-6.457	-1.370	-1.525	-5.907	-4.207	-6.388	-7.240
	(1.993)	(2.120)	(4.214)	(4.583)	(1.183)	(1.290)	(4.719)	(5.129)	(4.815)	(5.295)
Male		-0.061		0.130		0.110***		-0.065		-0.078
		(0.048)		(0.107)		(0.028)		(0.127)		(0.112)
Age		0.417**		0.188		0.126		-0.318		0.267
		(0.169)		(0.360)		(0.100)		(0.458)		(0.419)
Experience		0.001		0.001		-0.002		0.009		0.007
		(0.003)		(0.005)		(0.001)		(0.006)		(0.006)
Parent Entr.		-0.036		-0.032		0.051*		-0.018		0.051
		(0.047)		(0.103)		(0.029)		(0.126)		(0.121)
		0.025		0.106		0.017		-0.097		0.030
Married		(0.059)		(0.135)		(0.037)		(0.167)		(0.150)
		0.026		-0.001		-0.001		0.130**		0.061
Fam. Size		(0.021)		(0.045)		(0.012)		(0.053)		(0.050)
Observations	967	931	955	919	944	909	946	916	937	907

Note: The dependent variables are listed in the first row. All regressions include macro-area of learning and of current location and sector dummies. Regressions in even columns also include education dummies. Robust standard errors in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%. Significance levels: *: 10%, ** : 5%, *** : 1%

Table 10: Innovation and ED at learning age, ANIA sample

	(1)	(2)	(3)	(4)
	Share innov. sales		Innov. Score	
ED learn	0.248	-1.600	0.108	-7.111
	(0.584)	(1.010)	(3.913)	(6.379)
ED today	-1.103	-0.466	2.446	6.130
	(0.851)	(0.973)	(5.768)	(6.153)
Male		0.027		0.413***
		(0.019)		(0.148)
Age		-0.131*		-0.535
		(0.075)		(0.484)
Experience		-0.003***		-0.011
		(0.001)		(0.007)
Parent Entr.		0.016		0.018
		(0.020)		(0.134)
		0.020		-0.257
Married		(0.023)		(0.176)
		0.003		0.121**
Fam. Size		(0.008)		(0.059)
Observations	737	713	388	375

Note: The dependent variables are listed in the first row. All regressions include macro-area of learning and of current location and sector dummies. Regressions in even columns also include education dummies. Robust standard errors in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%. Significance levels: *: 10%, ** : 5%, *** : 1%

Table 11: Managerial practices and ED at learning age, ANIA sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Management		Monitoring		Targets		People	
ED learn	4.461**	1.956	6.115**	2.796	5.780**	3.370	3.396	2.097
	(2.160)	(3.422)	(2.727)	(4.419)	(2.931)	(4.681)	(2.122)	(3.359)
ED today	-0.571	1.370	-2.122	0.259	-3.213	-1.340	1.608	3.001
	(3.149)	(3.295)	(3.976)	(4.255)	(4.273)	(4.506)	(3.094)	(3.234)
Male		0.272***		0.321***		0.309***		0.191**
		(0.078)		(0.101)		(0.107)		(0.077)
Age		-0.195		-0.243		-0.035		-0.207
		(0.256)		(0.330)		(0.350)		(0.251)
Experience		-0.007**		-0.010**		-0.012**		-0.002
		(0.004)		(0.005)		(0.005)		(0.004)
Parent Entr.		-0.130*		-0.107		-0.104		-0.193***
		(0.071)		(0.092)		(0.097)		(0.070)
Married		0.067		0.038		0.075		0.143
		(0.093)		(0.120)		(0.128)		(0.092)
		0.073**		0.082**		0.058		0.068**
Fam. Size		(0.031)		(0.040)		(0.042)		(0.030)
Married	388	0.809	0.393	579	0.765	0.424		
Observations	388	375	388	375	388	375	388	375

Note: The dependent variables are listed in the first row. All regressions include macro-area of learning and of current location and sector dummies. Regressions in even columns also include education dummies. Robust standard errors in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%. Significance levels: *: 10%, ** : 5%, *** : 1%

A Appendix: Data details

A.1 The ANIA survey

The ANIA Survey for Small Business Companies collects data on a sample of 2,295 Italian firms and their top manager. The survey was conducted on a sample of small Italian firms, having up to a maximum of 250 employees, extracted from the total number of companies registered with CERVED - a business information agency operating in Italy which collects companies balance sheet data. The survey was conducted between October 2008 and July 2009.

Compared to the initial target set at the completion of 2,300 interviews, the investigation closed with 2,295 completed interviews. Participation in the survey entails the willingness to provide detailed information regarding many aspects of the firm's operations and characteristics as well as the willingness of the CEO/owner of the company to take part in a face-to-face interview with a professional interviewer. The first type of data was collected through a questionnaire filled out by each company, while the second type was obtained through an interview using the Computer Assisted Personal Interviewing method. Partly because the survey took place during the financial crisis and partly because interviews targeted the CEO of the firm, the drop out rate was relatively high particularly among firms in the larger size categories. To account for this the survey design was slightly reviewed to include a larger number of smaller firms (with less than 20 employees) which were easier targets. This has caused the sample to be somewhat biased towards smaller firms than the population of businesses with up to 250 employees.

A.2 The managerial practices survey

The data collection is based on a telephone double-blind survey technique and comprises a set of open-ended questions that are subsequently evaluated using a scoring grid. Qualitative answers are then recoded into quantitative measures with a score ranging between 1 (worst) to 5 (best managerial practices). We first set up a group of interviewers, trained them with a specific program and then had them run the survey. The data collection process was carried out using the methodology of the *World Management Survey*, `http://www.worldmanagementsurvey.com/` See Bloom and Van Reenen (2010a) and Bloom et al. (2012) for a full exposition of the survey characteristics and the data collection method.

Not all firms that were re-contacted participated to the management survey. A comparison of the observable characteristics of those who refused to participate and those who participated shows no systematic differences in terms of firm characteristics, sector, area of location and of learning. Some small but statistically significant differences emerge in terms of entrepreneurs' characteristics, such as education and having at least one parent that was an entrepreneur (see Table A.2.

A.3 Variables definition

Here we provide a detailed description of the variables used in the paper whose definitions are not obvious.

- *Entrepreneur, Def. I* This is a broaded definition which includes: self employed, partners of a company and owners that run an incorporated business.
- *Entrepreneur, Def. II* This is a narrowed definition that only include partners of a company and owners that run an incorporated business.
- *ED learn* Entrepreneurial density (number of firms per capita) in the location where the entrepreneur was living at age 18.
- *ED today* Current entrepreneurial density (number of firms per capita) in the location where the entrepreneur (or the firm in the case of the ANIA sample) is located.
- *LC learn* Log of bank branches per capita in the location where the entrepreneur was living at age 18. In Table 1 we report the mean and standard deviation of the level (rather than the log) of branches per 1000 inhabitants.
- *LC today* Log of current bank branches per capita in the location where the entrepreneur (or the firm in the case of the ANIA sample) is located. In Table 1 we report the mean and standard deviation of the level (rather than the log) of branches per 1000 inhabitants.
- *Number of income recipients* Members of the household who receive some income.
- *Mover* A dummy equal to 1 if current location of the individual is different from that in which she was born (SHIW sample) or was living at 18 (ANIA sample). In the SHIW sample, we distinguish between all individuals (Mover) and Entrepreneurs (Mover-Entrepreneur).
- *Years in control*: Number of years since the entrepreneur has acquired the responsibility of the management of the firm.
- *Risk aversion*: Indicator obtained using the answers to the question: "If the investment strategy of the firm depends only on you, among the following alternative strategies which one would you pick up? One that yields a) Low profits but no risk of losses; b) Decent profits and rare losses; c) Good profits with some chances of incurring losses; d) Very high profits with a high risk of significant losses." The indicator is coded between 1 and 4, increasing in risk aversion.
- *Ambiguity aversion* Indicator obtained using the answers to the question: "Think about two urns, each containing 100 balls, either green or yellow. You win 1,000 euros if you draw an urn of the color of your choice. Choose the color. Urn 1 contains both

green and yellow balls, in unknown proportion. Urn 2 contains 50 green and 50 yellow balls. From which urn would you rather draw the ball? a) Strong preference for urn 1; b) slight preference for urn 1; c) indifferent; d) slight preference for urn 2; e) strong preference for urn 2." The indicator is coded between 1 and 5, increasing in ambiguity aversion.

- *Confidence* Indicator obtained using the answers to the question: "With respect to the average ability of other entrepreneurs, in your job, do you believe to be: a) below average; b) average; c) above average." The indicator is coded between 1 and 3, increasing in self confidence.

- *Optimism*: answers to the question borrowed from a standard Life Orientation Test (Scheier et al., 1994): "How much do you agree with the statement: Overall I expect more good things than bad things to happen to me". Coded between 0 and 10, with a higher number indicating more optimism.

- *Satisfaction*: Indicator obtained from the following question: "Notwithstanding the profits motive and only considering the other characteristics of your job, can you tell me if they give you more satisfaction or dissatisfaction?" Coded between 0 and 10, with a higher number indicating more satisfaction.

- *Share of innov.*: Log of 1+ the share of sales in 2007 due to products or services either new or substantially improved, introduced to the market between 2005 and 2007.

Table A.1: First stage regressions for movers

	SHIW	ANIA
ED learn	-4.743***	6.484
	(0.546)	(5.121)
ED today	3.022***	-0.732
	(0.661)	(5.563)
LC learn	-0.020	0.101
	(0.014)	(0.221)
LC today	0.063*	0.527
	(0.036)	(0.0411)
Male	-0.015**	0.010
	(0.007)	(0.103)
Age	-0.137***	0.864**
	(0.041)	(0.440)
Experience	0.001	-0.004
	(0.001)	(0.005)
Parent Entr.	-0.019**	-0.129
	(0.008)	(0.100)
Married	0.036***	-0.286**
	(0.007)	(0.124)
Family size	-0.007**	0.023
	(0.003)	(0.044)
N. income	-0.010***	
recepients	(0.004)	
Local mobility	8.324***	29.607**
next 10 years	(2.597)	(14.594)
Local mobility	-6.336***	
past 10 years	(2.365)	
Observations	60,318	2,580

Note: the table reports the first stage probit regression in the Heckman selection model for the SHIW and ANIA sample. The dependent variable is a dummy equal to 1 for individuals that are currently resident in a province different form that of birth (SHIW) or in a LLS different from that in which the individual was living at 18 (ANIA). Local Mobility is the mobility rate out of the region (SHIW) or out of the municipality (ANIA). Next ten or past ten years refer to the average mobility at the local level in the ten years before or after the year in which the individual was 18. Both regressions include dummies for year, education, sector, macro area of birth (SHIW)/of learning (ANIA) and of current residence.

Table A.2: Comparison between re-interviewed and non re-interviewed entrepreneurs

	Re-interviewed			Non re-interviewed			
	N. Obs.	Mean	Std. Dev.	N. Obs.	Mean	Std. Dev.	Difference
TFP	388	2.511	0.836	579	2.416	0.948	0.096
Sales per worker	388	4.941	1.069	575	4.867	1.245	0.074
Employees	388	36.503	40.175	579	32.824	40.477	3.679
Dumsect1	388	0.036	0.187	579	0.024	0.154	0.012
Dumsect2	388	0.381	0.486	579	0.337	0.473	0.045
Dumsect3	388	0.010	0.101	579	0.009	0.093	0.002
Dumsect4	388	0.046	0.211	579	0.098	0.298	-0.052***
Dumsect5	388	0.240	0.427	579	0.247	0.432	0.007
Dumsect6	388	0.034	0.180	579	0.048	0.215	-0.015
Dumsect7	388	0.253	0.435	579	0.237	0.425	0.016
Dumarea1	388	0.307	0.462	579	0.316	0.465	-0.009
Dumarea2	388	0.302	0.460	579	0.297	0.457	0.004
Dumarea3	388	0.209	0.407	579	0.192	0.394	0.017
Dumarea4	388	0.183	0.387	579	0.195	0.397	-0.012
Dumarealearn1	388	0.291	0.455	579	0.314	0.465	-0.023
Dumarealearn2	388	0.291	0.455	579	0.287	0.453	0.005
Dumarealearn3	388	0.216	0.412	579	0.174	0.380	0.042
Dumarealearn4	388	0.201	0.401	579	0.225	0.418	-0.023
Education	388	14.031	2.570	579	13.377	2.547	0.654***
Age	388	51.716	11.107	579	50.421	10.119	1.295*
Male	388	0.722	0.449	579	0.663	0.473	0.058*
Parent Entr.	388	0.451	0.498	579	0.359	0.480	0.092***
Experience	388	20.649	11.301	579	19.036	10.868	1.613**
Married	388	0.809	0.393	579	0.765	0.424	0.044
Family size	375	3.093	1.197	556	3.043	1.159	0.050

Note: the table reports means and standard deviations of key variables for the sample of entrepreneurs that were re-interviewed and that were not. The last column report differences in mean. *** indicates significantly different at 1%, ** at 5%, * at 10%.

Table A.3: Entrepreneurial traits and TFP

		(2)	(3)	(4)	(5)	(6)
Risk aversion	-0.029					
	(0.045)					
Ambiguity aversion		0.013				
		(0.021)				
Confidence			0.078			
			(0.078)			
Optimism				0.011		
				(0.017)		
Satisfaction					0.016	
					(0.018)	
Share innov.						-0.034
						(0.022)
ED learn	3.515*	3.330*	3.575*	3.603*	3.255	4.762*
	(1.965)	(1.981)	(1.980)	(1.969)	(2.095)	(2.472)
ED today	0.133	0.074	0.247	-0.548	-0.191	0.199
	(3.130)	(3.135)	(3.208)	(3.179)	(3.202)	(3.611)
LC learn	0.070	0.071	0.072	0.045	0.055	0.183
	(0.124)	(0.125)	(0.126)	(0.127)	(0.126)	(0.140)
LC today	-0.342	-0.317	-0.341	-0.310	-0.321	-0.550**
	(0.244)	(0.244)	(0.246)	(0.252)	(0.252)	(0.272)
Male	-0.096	-0.105	-0.103	-0.096	-0.101	-0.070
	(0.065)	(0.066)	(0.066)	(0.066)	(0.067)	(0.075)
Age	0.272	0.287	0.256	0.263	0.225	0.401
	(0.229)	(0.231)	(0.233)	(0.233)	(0.242)	(0.272)
Years since	0.002	0.001	0.002	0.002	0.002	0.001
control	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Parent entr.	-0.099	-0.095	-0.101	-0.107*	-0.114*	-0.073
	(0.063)	(0.063)	(0.063)	(0.063)	(0.064)	(0.072)
Married	0.076	0.078	0.064	0.068	0.054	0.055
	(0.084)	(0.085)	(0.086)	(0.086)	(0.087)	(0.103)
Fam. size	0.022	0.022	0.027	0.024	0.023	0.025
	(0.027)	(0.028)	(0.028)	(0.027)	(0.028)	(0.033)
Observations	924	912	902	909	900	707

Note: All regressions include year, education, macro-area of learning and of current location and sector dummies. Significance levels: *: 10%, ** : 5%, *** : 1%

Table A.4: Managerial practices, TFP and firm size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	TFP					Employment (log)				
Management	0.177**					0.596***				
	(0.070)					(0.075)				
Monitoring		0.120**					0.477***			
		(0.057)					(0.057)			
Targets			0.087*					0.346***		
			(0.051)					(0.054)		
People				0.221***					0.523***	
				(0.076)					(0.081)	
Innovation					-0.005					0.082*
					(0.036)					(0.046)
ED learn	5.846*	5.859*	5.814*	5.922*	6.102**	2.663	2.545	2.366	3.114	3.857
	(3.032)	(3.020)	(3.027)	(3.011)	(3.028)	(3.795)	(3.627)	(4.032)	(3.840)	(4.100)
ED today	-3.307	-3.230	-3.070	-3.520	-3.122	-5.358	-5.152	-4.516	-5.699	-5.163
	(4.531)	(4.517)	(4.567)	(4.528)	(4.615)	(4.728)	(4.655)	(4.997)	(4.773)	(5.267)
LC learn	-0.036	-0.017	-0.018	-0.050	0.002	0.316*	0.366**	0.364**	0.320*	0.419**
	(0.142)	(0.141)	(0.142)	(0.139)	(0.139)	(0.161)	(0.161)	(0.166)	(0.167)	(0.179)
LC today	-0.052	-0.054	-0.031	-0.056	-0.027	0.028	0.007	0.097	0.043	0.093
	(0.310)	(0.312)	(0.306)	(0.310)	(0.306)	(0.328)	(0.326)	(0.335)	(0.336)	(0.351)
Male	-0.202**	-0.193**	-0.181*	-0.196**	-0.153	0.020	0.028	0.076	0.082	0.144
	(0.097)	(0.094)	(0.096)	(0.096)	(0.096)	(0.113)	(0.110)	(0.115)	(0.115)	(0.120)
Age	0.800***	0.813***	0.783***	0.802***	0.796***	0.578*	0.635**	0.513	0.581*	0.575*
	(0.266)	(0.266)	(0.268)	(0.263)	(0.266)	(0.319)	(0.321)	(0.332)	(0.328)	(0.338)
Years since	0.002	0.002	0.002	0.002	0.001	0.007*	0.007*	0.007	0.004	0.003
control	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Parent entr.	-0.173*	-0.181*	-0.185*	-0.154	-0.194**	0.087	0.066	0.050	0.108	0.009
	(0.095)	(0.096)	(0.095)	(0.095)	(0.096)	(0.102)	(0.103)	(0.104)	(0.105)	(0.109)
Married	-0.039	-0.029	-0.030	-0.061	-0.022	-0.054	-0.025	-0.031	-0.089	0.022
	(0.137)	(0.138)	(0.136)	(0.136)	(0.134)	(0.129)	(0.129)	(0.128)	(0.132)	(0.138)
Fam. size	0.037	0.039	0.044	0.035	0.049	-0.015	-0.012	0.007	-0.008	0.015
	(0.042)	(0.042)	(0.043)	(0.043)	(0.041)	(0.044)	(0.043)	(0.045)	(0.045)	(0.046)
Observations	370	370	370	370	370	370	370	370	370	370

Note: All regressions include year, education, macro-area of learning and of current location and sector dummies. Significance levels: *: 10%, ** : 5%, *** : 1%