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BORN IN HARD TIMES: STARTUPS SELECTION AND INTANGIBLE CAPITAL DURING THE FINANCIAL CRISIS

by Guzmán González-Torres, Francesco Manaresi, and Filippo Scoccianti*

Abstract

Credit availability is crucial for the birth and early development of startups. These often lack adequate collateral and are more exposed to a credit tightening than incumbents. While an extensive literature has shown how entrepreneurial selection, measured in terms of entrants' TFP, changes after a financial shock, technological adoption choices by new entrants might also be affected in the presence of a credit tightening. Using data for the universe of Italian corporations, we show that the credit crunch of 2007-2013 favoured the adoption of an intangible-intensive technology by newly-born firms. This new technology is characterized by a much higher capital efficiency. As a result, new firms were able to self-finance to a higher degree while reducing their reliance on external debt. While selection improved significantly during the credit crunch, technological adoption explains about one quarter of the observed evolution of aggregate productivity.

JEL Classification: D21, E22, G31, L11, O47.
Keywords: firm behavior, intangible capital, firm investment, aggregate productivity.
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Contents

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1 Introduction[1]

Credit markets shape aggregate productivity both in the short run (Ates and Saffie, 2016; Sedláček and Sterk, 2017) and the long run (Midrigan and Xu, 2014; Buera and Moll, 2015) by affecting entrepreneurs' ability to fund their ventures. Whilst the literature has extensively studied the roles played by investment and selection in firm total factor productivity as transmission mechanisms for financial shocks (Kiyotaki and Moore, 1997; Moll, 2014), technological adoption might provide an additional substantive channel (Araujo et al., 2019). The rate of adoption of a particular technology can depend on its ability to generate internal funds in the short run. In times of financial distress, technologies that lower firms' external dependence are likely to spread more rapidly. This channel might be especially relevant for new firms, which lack adequate collateral, and hence are more exposed to credit rationing. The adoption of new technologies by startups can thus be an effective strategy to cushion the impact of a credit supply shock. Could the large financial shocks observed in the last decade have driven technological adoption choices? If so, can we reconcile the evidence for individual and aggregate dynamics in terms of entry selection, adoption, and productivity?

Using detailed balance-sheet data for the census of Italian limited liability companies for 2005-17, we show that newly-born firms were more likely to adopt highly intangible, capital-saving technologies during the 2009-12 financial recession. Incumbents instead were less likely to invest in intangible assets, in line with previous findings (Ahn et al., 2018; Manaresi and Pierri, 2019). The newcomers that adopted a newer productive mix displayed significantly higher capital productivity, but only marginally higher total factor productivity. Additionally, by using a unique matched bank-firm-relationship dataset, we can causally trace the said findings to the credit supply shock endured by firms during the crisis. Based on this evidence, we build a model of firm dynamics with financial frictions in order to explore the mechanism behind the observed adoption dynamics, as well as the resulting aggregate effects. Prospective entrants randomly draw one of two production technologies, one being more intangible intensive than the other. Intangibility makes firms more efficient in their use of capital, reduces their financing needs, and increases their self-financing rate.

We find that the credit supply shock we identify in the micro data triggered a selection of entrants in favor of more capital efficient, intangible-intensive producers: Their entry rates declined by less, and their exit rates increased by less, than those of tangible-intensive firms. By calibrating the model to replicate our main empirical findings, we conclude that a credit supply shock reduces the number of startups, while at the same time causing an endogenous selection among prospective entrants. This favours the adoption of new production technology, characterized by a more intensive use of intangible capital and a higher self-financing rate.

We start by exploring how the crisis affected startup selection by identifying a set of stylized facts for cohorts of firms born during the 2007-2013 double-dip recession (henceforth, 'crisis cohorts'). We find that crisis cohorts are characterized by a higher intangibility of capital relative to both other cohorts at the same age, and other incumbents observed in the same year (also conditioning on industry- and province-level unobserved heterogeneity). This difference remains significant over the life of the firm, and we show that it stems from improved selection both at entry (tangible-intensive startups are less likely to enter during a financial crisis than before it) and over the first years of life (during the crisis, the risk of exiting within five years of age increases more for tangible-intensive firms than for intangible-intensive ones).

We then look at the characteristics of intangible-intensive startups. We identify two regularities that are

[1]We would like to thank Ufuk Akcigit, Matteo Bugamelli, Gian Luca Clementi, Silvia Giacomelli, Nezih Guner, Hugo Hopenhayn, Sebnem Kalemli-Ozcam, Salvatore Lo Bello, Francesca Lotti, Giacomo Rodano, Paolo Sestito, seminar participants at Bank of Italy and Paris School of Economics, and participants at the BoI-CEPR-EIEF workshop "Firm Dynamics and Economic Growth", the IMF-EIB-CompNet workshop "From Micro to Macro: Market Power, Firms' Heterogeneity and Investment", and the 7th CBRT-ECB Joint Conference on "Competition: Firm Dynamics, International Trade, Finance and Growth" for their insightful comments and discussions. The opinions expressed herein do not necessarily reflect those of the Bank of Italy.

present both before and during the crisis, as well as across industries. First, intangible intensity is a persistent feature: startups that have an above-the-median share of intangible capital also have a very high (73 per cent) probability of retaining it after 10 years of age. The likelihood that below-median startups remain that way at age 10 is even higher (around 80 per cent). Second, intangible capital is associated with higher capital efficiency: capital productivity (revenues-over-total capital) of firms with an above-the-median share of intangible capital is 20-40 per cent higher at any age. Consistent with these facts, we find that both capital productivity and TFP of cohorts born during the crisis is significantly higher than those of other cohorts. Additionally, the intangible intensity of the two groups of cohorts does not converge over time.

Next, we develop an empirical strategy to identify an exogenous shock to financing conditions that varies at the industry and province level. It helps us understand to what degree the observed patterns are determined by the financial nature of the recession rather than by demand-side factors like lower external demand or the uncertainty hike that took place during those years. We exploit the sudden interbank market freeze, which affected Italian banks after the subprime crisis of 2007 and the Lehman Brothers' default in 2008. This shock, largely unexpected in its depth and diffusion, increased the counterparty risk of interbank lending, effectively inducing a sudden freeze of this market (Brunnermeier, 2009). As a result, banks exposed with interbank liabilities could not roll over their debt and had to adjust their asset side by tightening the credit supply (Cingano et al., 2016). We exploit this exogenous shock and compute the pre-crisis exposure of each Italian industry-province pair as the weighted average of interbank-to-liabilities ratio of each bank, with bank weights equal to their share of credit granted to the industry-province cell. We show that the interbank exposure provides three measures of credit tightening for new and young firms during the double-dip recession: interbank exposure reduced the probability of acceptance of new credit applications, lowered credit granted to young firms, and increased the interest rate charged on it. We show that the interbank shock reduced the entry rates of new firms, and increased their intangible capital and productivity at entry.

Our empirical analysis is silent as regards the drivers of the adoption dynamics, since we do not observe the pool of potential entrants. The firm dynamics model we build, based on Clementi and Palazzo (2016), illustrates how technological adoption can help firms buffer a credit supply shock. Potential entrants to a market receive a signal of their random future productivity, as well as access to one of two existing technologies. These differ in the effective units of capital that any given mix of tangible- and intangible capital yield. *Intangible intensive* firms are more elastic to intangible capital. Additionally, they require fewer inputs overall to achieve a certain level of effective capital. In line with the empirical findings, these firms achieve substantially higher capital productivity and profitability, but only a slightly higher revenue productivity.

Firms face financial constraints in the model. Producers that invest beyond their current profits have to rely on external finance. The cost of external funds has three components: a constant that is equal across borrowers, a proportional one that increases with the amount of borrowing, and a component that lowers the cost of borrowing with the amount of tangible capital installed. External funding is thus costlier than reinvesting internal funds. Tangible-intensive firms, which use more total capital per unit of output, are typically more leveraged. This is especially true in the early stages of life when firms also have little tangible capital.

We calibrate our economy to replicate the main empirical facts. We then use it to simulate an increase in external financing costs comparable to that observed in the data. The model predicts a rise in the share of intangibles for new cohorts of 5 percentage points for ages 0 through 10 years. There are two channels at play. First, tangible-intensive firms tend to select more starkly at entry. Given their higher leverage, the financial cost hike discourages potential entrants with lower productivity signals from entering the market. Even though the entry rate of intangible-intensive firms also drops, it does so less than for the former.

Second, higher financing costs impact more on tangible-intensive firms not only at entry but also during their whole life cycle, leading to a larger increase in their exit rates at any age relative to that suffered by intangible-intensive firms. Since both changes in entry and exit rates after the shock are relatively unfavorable to tangible-intensive firms, a composition effect emerges, whereas new cohorts are skewed towards intangible-intensive types. Since new cohorts of firms have a structurally higher share of intangible capital, on aggregate, the financial shock causes a persistent increase in intangible goods accumulation.

Our paper contributes to the literature that studies how pro-cyclical net entry plays a major role in amplifying the effects of aggregate shocks, see Clementi and Palazzo (2016), as young firms contribute disproportionally to input and output growth, see Calvino et al. (2018). This amplification effect may be partially reduced by the counter cyclical selection of new startups. It has been widely shown that downturns have a cleansing effect by forcing the exit of less efficient firms and by imposing fiercer selection at entry (Lee and Mukoyama, 2015). Most of the literature on the selection of startups and young firms during downturns, however, focused on recessions caused by an aggregate productivity shock.[2] Yet financial crises may have peculiar implications for young firms. Indeed, they are more likely to be credit constrained (Hadlock and Pierce, 2010), as they need to raise proportionally more capital to sustain their first years of growth and banks tend to cut credit proportionally less to incumbents that benefit from established credit relationships (Bolton et al., 2016). Our paper shows that intangible-intensive firms are more resilient to external financing shocks, as they have higher capital productivity and thus less leverage at entry.

Our paper also contributes to the literature that studies the characteristics of start-up firms over the business cycle by focusing on the cyclicality of intangible investment and credit constraints, see Aghion et al. (2010, 2012). While the latter strand of the literature focuses on the cross-sectional behavior of firms over the cycle, we concentrate on new cohorts of firms born during the financial shock. We also contribute to the broader and flourishing literature on startups, see Sedláček and Sterk (2017), by concentrating on a novel empirical fact–intangible investments after a credit restriction–and on how this can be rationalized by both conditions at birth and post-entry choices.

The remainder of the paper is structured as follows. Section 2 presents the main data sets used in our empirical analysis. Section 3 presents a set of stylized facts for new cohorts of firms born during the crisis. Section 4 presents a quasi-natural experiment that exploits an interbank market shock to show the causal relation between the credit supply shock and the behaviour of new cohorts of firms in several dimensions relevant to our analysis. Section 5 presents the theoretical model, and Section 6 performs a quantitative exercise aimed at mimicking the financial shock. Section 7 concludes.

2 Data

We exploit detailed information on yearly balance sheets and income statements from CervedGroup SpA (Cerved database). Our data covers the census of Italian incorporated firms over the period 1998-2016. We study the life cycle dynamics of all cohorts of firms born during our period of analysis and for which we observe at least 5 years of data (i.e. cohorts from 1998 to 2011). We focus on firms active in manufacturing, construction, and private non-financial services.[3] For every individual year, we select firms that report positive revenues and assets. The resulting database covers 1,460,777 unique firms over 18 years (more than 600,000 firms per year). Table 1 summarizes the main variables of interest for our final sample. All data are in 2010 prices. Labor is proxied by a firm's total wage bill, while capital is proxied by total fixed assets (both tangible and intangible). Capital intangibility is the share of intangible capital over total fixed assets.

[2] At the same time, the existing analyses of the cleansing effect during a financial recession do not focus explicitly on new and young firms (Osotimehin and Pappadà, 2015; Foster et al., 2016).

[3] NACE Rev.2.2 Sections C, F-J, and L-N.

Table 1: Descriptive statistics for our sample

Variable	Mean	Median	St. Dev.
Revenues	955.66	135.72	2286.22
Value Added	232.02	25.31	658.84
Labor	136.57	10.37	319.19
Capital	204.53	13.32	680.37
Intangible Share	0.25	0.07	0.33

Source: Cerved

We try to identify what types of investments are included among intangibles. According to Italian law, firms should include the following in this category: R&D expenditures, software, the value of patent rights, trademarks and industrial designs (either owned or granted), goodwill and setting up costs, and amortization of past intangible investments (net of goodwill and setting-up costs). Detailed information is available for a share of firms. Before 2015, it was available for less than 20per cent of them , while starting in 2015 (when tax credits on specific types of intangibles were enacted) the number of firms reporting details on intangibles increased to more than 50 per cent. Figure 2 reports the share of intangibles by type in two prototypical years: 2005 and 2015. The majority of intangibles are unspecified in nature, while among those that are identified, most are either current expenditures on R&D, intellectual properties, and software or amortization of previous expenditures of this kind. Given the small share of firms reporting intangible types, for our baseline results we do not distinguish by intangible type. As a robustness check, we have focused on firms that report intangible types and have excluded goodwill and setting-up costs, to focus on more strictly 'innovative' elements. All our results remain remarkably unaltered.

3 Stylized Facts

Figure 4 plots the share of intangible over total fixed capital for each cohort of firm born during the period of analysis and observed for at least 5 years, controlling for province and sector unobserved heterogeneity. It shows that the share of intangible assets increases markedly, starting from the cohort of 2007 onwards. Importantly, this difference does not revert over the life cycle of firms. Pre-crisis and crisis cohorts seem to converge to two different levels of intangibility of capital (shown in the Figure as A and B respectively). Figure 5 shows the results of the difference in intangible shares between crisis and non-crisis cohorts, after controlling for province, sector, and year fixed effects. The difference remains large and significant throughout the observed life of the firms. The inclusion of year fixed effects implies that the difference is significant both relative to other cohorts in previous years and to older firms in the same year. Thus, it is not the result of an aggregate shock affecting the whole economy, but: a cohort-specific difference.

As further evidence of this, Figure 6 plots the average share of intangible capital of startups and incumbents overtime. While the crisis induces a significant rise in the intangible share of entrants (+4 percentage points), the intangible share of incumbents drops marginally (by around half of a percentage point). Moreover, the rise in the intangible share by entrants is reversed from 2014 onward, providing evidence that it may be closely linked to the crisis.

We study more in depth whether the increase in intangible shares of cohorts born during the crisis stems from selection at entry or arises over the life cycle of firms. We distinguish between tangible-intensive and intangible-intensive startups as those that have a below- or above-median ratio between intangibles and total

Table 2: Persistence of cohorts in a high/low intangibility status - cohorts born before the crisis

		Age 10	
		Low	High
Age 1	Low	70.32	29.68
	High	20.25	80.75

Notes: Low/high intangibility refers to being below/above the median share of intangible over total fixed capital of each specific cohort at the specified age (namely, age 1 or 10).

capital, respectively.[4] We then plot entry rates for both types of firms. Figure 7 shows that entry rates of tangible-intensive firms dropped more markedly. Firm exit also seems to play a role: Figure 8 plots the relative risk of exiting for high- vs low-intangible firms both before and during the crisis.[5] We obtain two results: first, the relative risk of exiting is generally higher for intangible-intensive firms. This could stem from the higher risk of entrepreneurial activities based on innovative capital, such as patents or R&D. Second, during the crisis, the exit rates of tangible-intensive firms increased more than that of intangible-intensive ones. This is why the relative risk of exit decreased across all ages during the crisis.

These results could be confounded by firms switching from above to below the median of tangibility over time, and vice versa. This could be the case if, for instance, intangible capital investment were lumpy. In this case, being high-intangible one year would be negatively correlated with being high-intangible in the following one. However, it turns out that intangibility is a highly persistent feature of firms. Table 2 shows that over 70 per cent of firms born as low-intangible remain so after 10 years of life. Table 3 shows that, by and large, the same applies to the cohorts born during the crisis.

A second important feature of intangible capital is that it is more productive than tangible capital. This can be appreciated if we look at capital productivity, measured as revenues over total fixed capital. Figure 9 shows the difference in capital productivity with respect to the baseline category, namely tangible-intensive firms at age 1, after controlling for year, province, and sector fixed effects. There is a wide difference between the two groups, ranging between 25 to 40 per cent, and it is strongly persistent overtime. Significant differences can also be found in terms of total factor productivity: Figure 10 shows the differences in TFP between intangible-intensive and tangible-intensive firms by age.[6] The differences are around 2.5 per cent in a firm's first 2 years, and then decline to 0.5 per cent at year 10, but remain statistically significant and economically relevant, as they represent around 15 per cent of the within-sector-and-province variability of TFP. Greater capital productivity of intangible-intensive firms results in a lower capital-to-labor ratio, as shown in Figure 13.

Given the persistent productivity differential of high-intangible firms, and the increase in their share among crisis cohorts, it comes as no surprise that these cohorts display greater productivity throughout their life relative to pre-crisis cohorts (and net of sector, province, and year fixed effects). Figures 11 and 12 show that this is indeed the case, in terms of both capital productivity and TFP.

Finally, by exploiting the availability of detailed financial statements, we study firm leverage for high- and low-intangible firms over their life cycle, both before and during the crisis. We measure leverage as the ratio between total assets and networth.[7] The first finding is that leverage declines with firm age, a fact recently

[4]The median value is measured before the crisis, i.e. over the period 1999-2006.

[5]Importantly, these results are obtained after partialling out unobserved industry and province heterogeneity.

[6]TFP has been calculated as the residuals of a trans-log production function estimation, obtained using the method developed by De Loecker and Warzinsky (2009), with an additional instrument to overcome the identification problem discussed by Gandhi, Navarro and Rivers (2016). Details of the estimation and its output are available upon request.

[7]As in the other analyses in this paper, we control for sector, province, and year unobserved heterogeneity. The results are nonetheless invariant to different fixed-effects structures, as well as to not conditioning for any type of unobserved heterogeneity.

Table 3: Persistence of cohorts in a high/low intangibility status - cohorts born during the crisis

		Age 10	
		Low	High
Age 1	Low	72.71	27.29
	High	21.39	78.61

Notes: Low/high intangibility refers to being below/above the median share of intangible over total fixed capital of each specific cohort in the specified age (namely, age 1 or 10).

identified for US private firms, too (Dinlersoz et al., 2018). Secondly, the left-hand panel of Figure 14 shows that, before the crisis, tangible-intensive firms had higher leverage at entry and for the first four years of life. Their leverage declined more steeply over the age distribution, thus by the age of five, intangible-intensive firms were more leveraged. The right-hand panel of the figure shows that the crisis had a significant negative effect on the leverage of tangible-intensive firms, which dropped from 6 to around 5 at entry. Conversely, intangible-intensive firms were unaffected. In Section 5 we are able to replicate and rationalize all these facts within a Hopenhayn-type model that features two types of capital, two technologies, and a shock to external finance.

Before presenting the model, however, we need to provide clear-cut evidence that it was indeed the shock to the supply of external finance (notably, credit) that induced these selection processes among crisis cohorts.

4 The Role of the Financial Shock: Evidence from a Natural Experiment

These patterns may stem either from the financial nature of the double-dip recession in Italy or from demand-side channels that negatively affected the economy in those years, such as the drop in foreign demand. Identifying the driver of the selection at entry is important to correctly understand the functioning of the economy and, possibly, to design adequate policies to counter the negative effects of recessions (either financial or non-financial). Our data prevents us from studying previous significant non-financial recessions (the only large recession was in 1992; the recession of the early 2000s does not seem to have had a significant impact on intangibility, yet the dot-com bubble only mildly hit Italy and for a very short period of time).

Thus, we rely on a different strategy. We devise an empirical methodology to identify a plausible proxy of the way in which the financial shock hit the Italian economy, and we put it in relation to our variables of interest, namely entry rates, the intangible intensity of new entrants, and their productivity. This proxy is the exposure to the interbank shock.

The cost of interbank funding increased markedly during the financial crisis: as a result of the subprime crisis in 2007 and of the Lehman Brothers default in 2008, there was an increase in perceived counterparty risk and the volumes of liabilities exchanged on the market plummeted. Even the Italian banks that were not directly exposed to toxic assets, Special Purpose Vehicles, or Lehman's liabilities, markedly suffered the freeze of this market. Average deposits in the interbank markets of Italian banks dropped from over 20 billion per day in 2016 to less than 4 billion in 2010.

Several empirical studies have exploited this freeze as a natural experiment to test the strength of the bank lending channel (Bernanke and Gertler 1995) and its real effects.[8] All these research papers exploited detailed bank-firm data to construct a firm-level measure of pre-crisis exposure to the interbank market, usually

[8]See for instance, Ivashina and Scharfstein 2010; Bonaccorsi di Patti and Sette 2012; Iyer et al. 2014; Kapan and Minoiu 2013; Cingano et al. 2016; Manaresi and Pierri 2018.

defined as the weighted average of interbank liabilities-to-assets of each lender, weighted by its share of total credit granted to the firm. The resulting idiosyncratic firm-level shock to credit supply has largely been proved to be strong (greater firm-level exposure to the interbank market freeze predicts negative credit growth and, sometimes, higher interest rates) and exogenous (uncorrelated with observable and unobservable firm and bank characteristics, as well as some indicators of firm investments and demand expectations). Our interest, however, differs from previous studies: while they all focused on incumbent firms, we study new startups. These firms often do not have any existing relationship with a bank and, thus, idiosyncratic indicators at firm level cannot be measured. Moreover, we are particularly interested in the extensive margin of the impact: i.e. the possibility that credit tightening prevents firms from entering the market. For this reason, we have to exploit a local level measure of exposure to the interbank market. In particular, we compute the province-sector interbank exposure by averaging the 2006 interbank liabilities-to-assets ratio of each bank with weights equal to the share of credit granted by the bank to that province-sector cell in 2006. Formally,

$$IT\bar{B}K_{p,s,2006} = \sum_b \frac{C_{bps,2006}}{C_{ps,2006}} ITBK_{b,2006} \tag{1}$$

We then use this variable in a panel regression as follows:

$$Y_{p,s,t} = \psi_{ps} + IT\bar{B}K_{p,s,2006} \times \lambda_t \gamma + [X_{pst-1}\beta] + \varepsilon_{p,s,t} \tag{2}$$

where Y_{pst} is a dependent variable measured at the province, sector and time level, and we control for sector, province, and year fixed effects. We alternatively restrict, and do not restrict for a set of lagged controls at the province-sector-year level to test the robustness of our results.[9] We standardize the interbank exposure variable to simplify the interpretation of the results.

We group our results into two figures: the first shows that the interbank exposure has an effect on the credit access of new firms (i.e. our experiment has statistical strength), and the second shows its effect on new cohorts of entrants. Incidentally, because we also plot estimates for pre-crisis years, we find that the interbank exposure has no effect before the financial crisis (a reassuring placebo test). Figure 15 shows that the interbank exposure does affect credit tightening during the recession (and not before it). Panel (a) plots the coefficients of the interbank exposure variable in each year, using the probability of a credit application being accepted as the dependent variable. Panel (b) plots the results on log credit granted by banks to young firms (lower than 3 years old), while Panel (c) shows the results for interest rates charged on these loans. The results show that a one standard deviation increase in interbank exposure reduces the probability of a new credit application being accepted by around 2 percentage points. Once the application is accepted, a one standard deviation increase in interbank exposure reduces total credit granted by around 15 per cent and raises interest rates by around 0.5 percentage points.

Panel (a) of Figure 16 shows that the interbank shock during the crisis reduces entry rates by 1-1.5 percentage points. The effect is statistically significant for the years 2007-2009 and 2011-2012. It is not significant during the small recovery of 2010, nor at the end of the crisis. Panel (b) shows that the drop in entry rates is accompanied by an increase in the intangibility of capital at entry; panel (c) shows that this increase is correlated with higher capital productivity.

5 Model

General Setup

We enrich the model by Clementi and Palazzo (2016) with two types of capital, tangible m_t and intangible i_t, an external financing cost function as in Gomes (2001) augmented with tangible capital as collateral, tangible

[9]Controls include log number of firms, log sales, log sales growth, and the Herfindahl-Hirschman index of sales.

capital irreversibility, and two technologies: one that uses more intangibles than the other.

The economy consists of a continuum of heterogeneous firms that produce a single output that can be used for consumption or as either type of capital using a span of control[10] technology

$$f(k_t, l_t) = s_t \left(k_t^{\alpha} l_t^{1-\alpha}\right)^{\nu}$$

where α represents the capital income share and the span of control parameter ν defines the returns to scale of firms. Total firm capital is made up of tangible and intangible capital, which are combined using the following aggregator

$$k_t = \left(\theta^m (m_t)^{\rho} + \theta^i (i_t)^{\rho}\right)^{\frac{1}{\rho}} = \left(\theta^m + \theta^i\right)^{\frac{1}{\rho}} \left(\frac{\theta^m}{(\theta^m + \theta^i)} (m_t)^{\rho} + \frac{\theta^i}{(\theta^m + \theta^i)} (i_t)^{\rho}\right)^{\frac{1}{\rho}}$$

i.e. tangible and intangible capital are substitutable with elasticity ρ. The parameters θ^m and θ^i measure the relative productivity of each type of capital. In this version of the model with two technologies, the relative productivity of intangible capital can take two values, $\theta^i \in \left\{\theta_L^i, \theta_H^i\right\}$. Note that in the case of $\rho = 0$, the capital aggregator becomes

$$\lim_{\rho \to 0} k_t = \left(\theta^m + \theta^i\right) m_t^{\frac{\theta^m}{(\theta^m+\theta^i)}} i_t^{\frac{\theta^i}{(\theta^m+\theta^i)}}$$

and the production function correspondingly takes the form

$$f(m_t, i_t, l_t) = \tilde{s_t} \left(m_t^{\tilde{\theta^m}} i_t^{\tilde{\theta^i}} l_t^{1-\alpha}\right)^{\nu}$$

where $\tilde{s_t} = s_t \left(\theta^m + \theta^i\right)^{\alpha\nu}$, $\tilde{\theta^m} = \theta^m \frac{\alpha}{(\theta^m+\theta^i)}$, $\tilde{\theta^i} = \theta^i \frac{\alpha}{(\theta^m+\theta^i)}$, which retains the span of control formulation.

Firms are subject to idiosyncratic exogenous productivity shocks, governed by the process:

$$\ln s_{t+1} = \rho_s \ln s_t + \varepsilon_t^s,\ \varepsilon_t^s \sim N(0, \sigma_s)$$

Potential entrants receive a signal $q \sim G(q)$ regarding their potential first period idiosyncratic productivity, such that:

$$\ln s_{entrant} = \rho_s \ln q + \varepsilon_t^s,\ \varepsilon_t^s \sim N(0, \sigma_s)$$

In addition, potential entrants draw a value θ_I^i, $I \in \{L, H\}$ with probabilities $\{p_i, 1 - p_i\}$ respectively. Idiosyncratic productivity shocks are independently drawn across firms. Static profits are given by

$$\pi(s_t k_t, l_t) = \max_{l_t} s_t \left(k_t^{\alpha} l_t^{1-\alpha}\right)^{\nu} - w l_t$$

The aggregate state of the economy can be summarized as follows:

$$\Lambda_t = \{\Gamma_t(m, i, s, I)\}$$

where $\Gamma_t(m, i, s, I)$ represents the distribution of firms in the economy with respect to their individual state variables.

Firm investment in either capital type (indexed by $j = \{m, i\}$) is defined as:

$$x_t^j = j_{t+1} - (1 - \delta_j) j_t$$
$$x_t = \sum_{j=m,i} \chi_x\left(x_t^j\right) x_t^j$$

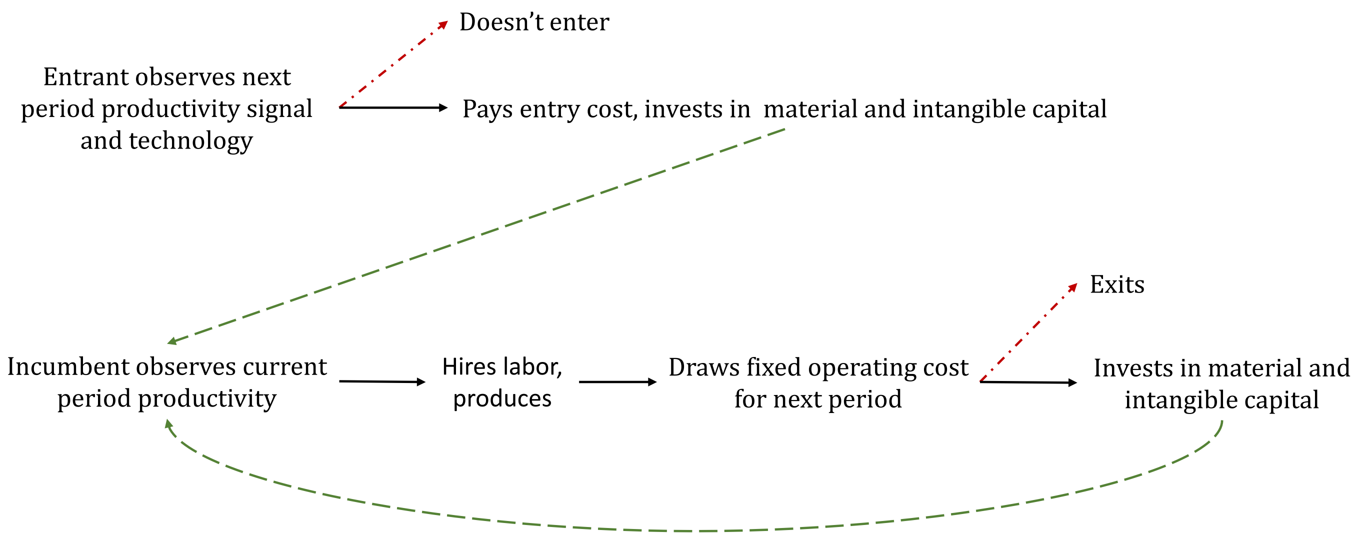
$$\chi_x(a) = \begin{cases} 1 & , |a| > 0 \\ 0 & , otherwise \end{cases}$$

[10]See Lucas Jr (1978).

where δ_j represents the depreciation rate of each capital type, and x_t represents total firm investment expenditures. Firms that adjust their capital stocks bear the cost of investing $g\left(x_t^m, x_t^i, m_t, i_t\right) > 0$, $\forall x_t > 0$.

Firms face external financing costs as in Gomes (2001), i.e. the firm bears a positive cost $\phi\left(e_t; m_t\right) > 0$, $\forall e_t \equiv x_t + g\left(.\right) - \pi\left(.\right) > 0$ when using external finance and $\phi\left(e_t; m_t\right) = 0$, $\forall e_t \leq 0$ whenever making non-negative profits after investment. Additionally, financing costs are increasing in the amount the firm finances, i.e. $\frac{\partial \phi(e_t;m_t)}{\partial e_t} > 0$, but decreasing in the amount of tangible capital of the firm, i.e. $\frac{\partial \phi(e_t;m_t)}{\partial m_t} < 0$. This last assumption is a proxy for the firm being able to pledge tangible capital as collateral for external financing operations.

Timing of the Model



Given the recursive nature of firms' problems, we henceforth drop all time subscripts.

Incumbents At the beginning of a period, incumbents observe their exogenous productivity shock s_t. Accordingly, firms choose how much labor to hire, how much to produce, and their corresponding revenues. Firms' beginning-of-period value function is thus given by:

$$V\left(m, i, s, I\right) = \max_l s\left(k^\alpha l^{1-\alpha}\right)^\nu - wl + \int V_c\left(m, i, s, I\right) dG\left(c_f\right)$$

where the choice of labor is completely static. $V_c\left(m, i, s\right)$ represents the expected option value of choosing to re-enter the market at the end of the period:

$$V_c\left(m, i, s, I\right) = \max\left\{V_{exit}\left(m, i\right), V_{invest}\left(m, i, s, I\right) - c_f\right\}$$

In the event of choosing to exit, firms recuperate the non-depreciated capital outstanding from production, minus the corresponding adjustment costs:

$$V_{exit}\left(m, i\right) = \sum_{j=m,i} j\left(1 - \delta_j\right) - g\left(-m\left(1 - \delta_m\right), -i\left(1 - \delta_i\right), m, i\right)$$

The value of re-entering the market, and undertaking the corresponding investments, is given by:

$$V_{invest}\left(m,i,s,I\right)=\max_{x^m,x^i}-x-g\left(.\right)-\phi\left(.\right)+\frac{1}{R}\int_s V\left(m',i',s',I\right)dH\left(s'|s\right)$$

Entrants Potential entrants draw a technology θ_I^i and receive a signal on their potential productivity in the following period. The value of entering the market is then given by:

$$V_{entry}\left(q,I\right)=\max_{m',i'}-x-\phi\left(x;0\right)+\frac{1}{R}\int_s V\left(m',i',s',I\right)dH\left(s'|q\right)$$

Functional Forms

We need to specify concrete functional forms for the investment adjustment cost and the external financing cost functions. We assume the following shape for the investment adjustment cost function:

$$g\left(x^m,x^i,m,i\right)=\sum_{j=m,i}\chi_x\left(x^j\right)\left(c_0+c_1\left(\frac{x^j}{j}\right)^2\right)j+\chi_m\left(x^m\right)c_2 m$$

$$\chi_m\left(a\right)=\begin{cases}1 & ,a<0\\ 0 & ,\, otherwise\end{cases}$$

with $c_0,c_1,c_2>0$. Firms face three types of costs when adjusting their tangible and intangible capital: $c_0 j$ represents a fixed cost of adjusting either type of capital. Additionally, firms face a convex adjustment cost $c_1\left(\frac{x^j}{j}\right)^2 j$. Finally, tangible capital is partially irreversible, as scaling it down implies an additional fixed cost $c_2 m$.

We posit the following functional form for the external financing costs of firms:

$$\phi\left(e;m\right)=\chi_m\left(-e\right)\left(\phi_0+e\phi_1\exp\left\{-\phi_2\frac{m}{e}\right\}\right)$$

where $\phi_0,\phi_1,\phi_2>0$. As in Gomes (2001), firms face a fixed cost ϕ_0 of resorting to external finance, and a linear variable cost $\phi_1 e$. Additionally, the term $-\phi_2\frac{m}{e}$ captures the idea that tangible capital can be used by firms as collateral in order to lower the total cost of external financing, with ϕ_2 representing the efficiency of the financial system in terms of accepting collateral.

6 Quantitative Exercise

Calibration

The set of calibrated parameters can be divided into two groups: one that consists of parameters taken directly from the data, and another where parameters are jointly estimated to match relevant statistics. The depreciation rates for both types of capital, 8.4 per cent for materials (δ_m) and 17.9 per cent for intangibles (δ_i), are taken from the National Accounts. The shares of intangibles in the Cobb-Douglas capital aggregator are set to obtain, in equilibrium, an average share of intangibles over total capital equal to 27 per cent for intangible-intensive firms and to 16 per cent for tangible-intensive ones. The overall efficiency of capital is chosen so as to make total capital installed 20 per cent more productive for intangible-intensive firms.

The share of capital in production is set at 30 per cent while the span-of-control parameter ν, i.e. the degree of returns to scale, is chosen to equal 0.8, a number commonly used in the literature. Convex adjustment costs for capital investment are chosen to obtain lumpy investment. They are set equal to the values in Clementi and Palazzo (2016). We choose the persistence of idiosyncratic productivity shocks, ρ_s, to equal 0.55, in line with

Table 4: Parameter Values

Parameter	Variable	Value
δ_i	depreciation rate intangibles	0.179
δ_m	depreciation rate materials	0.084
ν	returns to scale	0.8
ρ_s	persistence idiosync. shocks	0.55
$g(.)$	K-adjustment costs	1.14% variable; 0.0011 fixed
α	total capital share	0.3
ξ	elasticity of labor supply	2.0

Clementi and Palazzo (2016). The volatility of the shocks is chosen so as to obtain in equilibrium an average of 80 per cent of indebted firms in the sub sample of firms younger than 5 years.

The proportional cost of finance is fixed to approximate the average interest rate charged on loans to non-financial corporations before the crisis, while the fixed costs of financing are chosen to match the average debt-over-asset of start-ups in the economy before the crisis (11 per cent). We set the proportional cost of finance at 2 per cent and the fixed cost at 0.005 in the baseline steady state. The financial shock is simulated through an increase in both these costs: the proportional financing cost increases to 6 per cent, in line with the average interest rate charged on loans to non-financial corporations during the crisis, while the fixed cost is increased to match the fall in start-ups' debt-over-assets from 11 per cent before the crisis to 8 per cent afterwards.

Model Results

The global financial shock that hit the Italian economy in 2007-8 was unexpected and persistent, lasting–once the sovereign debt crisis is factored in–at least up until 2013. The high persistence of the shock led us to choose an exercise that revolves around the simulation of two steady states. The first one is meant to represent the pre-crisis economy and is characterized by a low level of external financing costs, while the second one has a high level of external financing costs set to mirror the across-the-board restriction in credit supply which took place after 2007. The model is built to deliver selection both *within* and *between* firms, and to shed light on the mechanics behind the increase in the share of start-ups with intangible-intensive intensity.

Main Features of the Economy While the model by construction replicates certain features of the economy in steady state, like the average cross-sectional share of intangibles over total capital in the economy, the features that matter most for the analysis are left unrestricted and are generated endogenously by the simulation exercise. Chief among those features is the dynamics by age of input accumulation and of the exit rates. Since they are crucial to understanding how the economy will react to a financial shock, we briefly review how far the model goes in approximating the dynamics by age of the most important variables. The model replicates the dynamics of accumulation by age of both tangible and intangible capital and hence the share of intangibles over total capital (given by the sum of materials and intangibles). Figure 20a shows the declining path by age of the average share of intangibles over total capital for a cohort of firms. This path stems from the slower accumulation of materials with respect to intangibles. The different speed at which the two capital inputs are accumulated stems from the expected path of TFP. Firms enter the market with a TFP level that is below the unconditional mean of the stochastic process driving the productivity shocks. Over time, productivity converges to its unconditional mean, so that the average TFP by age of incumbents is upward-sloping and concave. Firms perfectly forecast this increasing path and accumulate the more elastic input, i.e. tangible capital, more slowly. Investment in the latter accelerates as firms age, thus lowering the share of intangibles over total capital. Over time, the share of the two inputs stabilizes and reaches its long-term equilibrium, which equals the ratio of the two inputs' Cobb-Douglas elasticities.

The capital of intangible-intensive firms has higher efficiency units, which implies a smaller capital-intensiveness: intangibles are a capital-saving technology. Accordingly, their capital-labor ratio is lower (Figure 27), replicating the evidence from the data (Figure 13). Higher capital efficiency and hence lower capital-intensiveness are crucial features for understanding the different reactions to a financial shock by the two types of firms.

We calibrate the model in order to obtain an equal share of prospective entrants between tangible- and intangible-intensive firms. However, over time the composition of the economy between the two types of firms changes, as exit rates differ in intangible intensity. Firms exit whenever they draw an operating cost such that the value of exiting is greater than the value of continuing operations. Both the value of continuing and exiting are increasing and concave in capital, but the former grows faster with capital, see Clementi and Palazzo (2016). Given this exit mechanism, the model is suited to endogenously replicate higher exit rates for intangible-intensive firms (see Figure 17) since they are less capital intensive at any age. This implies that the share of tangible-intensive firms grows over time, as companies with intangible-intensive intensity are structurally more likely to exit the market. Moreover, since the exit rate for intangible-intensive firms is higher, especially at young ages, even in the presence of an equal share of prospective entrants between the two types of firms, at age 1 there will be more tangible-intensive than intangible-intensive firms in the market (see Figure 19a). Indeed, many intangible-intensive prospective entrants will immediately exit the markets after observing their productivity signal.

In the following section, we explore the effect of a financing shock on the selection of firms and on the share of tangible- versus intangible-intensive producers in new cohorts.

The Effect of a Financial Shock We simulate an increase in financing costs that mimics the financial shock suffered by the Italian economy in 2007-8. We do so by increasing the fixed and proportional components of the financing cost function in order to match the estimated fall in the leverage of start-ups during the crisis.

Ceteris paribus, higher financing costs lower the profitability of firms. As a result, prospective entrants' value of becoming an entrepreneur decreases. Crucially, the entry value falls relatively more for those firms that are more capital-intensive and hence leveraged: tangible-intensive firms. Figure 28 shows new cohorts' average leverage by age, calculated as the amount of external finance divided by total capital (tangible plus intangible), both before and after a financial shock. Before the crisis, and up to age 3, tangible-intensive firms are more leveraged than intangible-intensive ones. This is confirmed by the data (see Figure 14), where leverage has been calculated as assets over net worth. A fraction of tangible-intensive firms that, before the shock, could enter the market with a relatively low level of TFP, are no longer able to do so. Only tangible-intensive firms with a high enough TFP level have a self-financing rate that is sufficient to limit their external financing costs: therefore, the average TFP of tangible-intensive firms at entry increases considerably (see Figure 18), and their average demand for credit decreases (see again the right-hand panels in Figures 28 and 14) for this decline in the model and in the data.

This selection in productivity *within* tangible-intensive establishments also implies a selection *between* tangible-intensive and intangible-intensive firms. Indeed, positive selection at entry for tangible-intensive corporations comes at the expense of their numerosity, which decreases sharply. On the other hand, since intangible-intensive firms have a lower capital-labor ratio and a lower leverage at entry, thanks to the higher efficiency units of their total capital, they do not need to further increase their profitability or their self-financing rate at entry to absorb the increase in financing costs. Hence there is no within selection in TFP at entry among intangible-intensive firms and their mass remains constant[11].

The average total factor productivity at entry of tangible-intensive establishments increases by almost 10 per cent. Moreover, exit rates also increase relatively more for tangible-intensive firms after the financial shock. This second effect is also related to the higher capital intensity and leverage of those firms, which increase their vulnerability to financial shocks. The combined effect of lower entry and higher exit rates leads to a change in the proportion of tangible-intensive versus intangible-intensive firms in new cohorts, as shown in Figure 19. The 8 percentage point increase in the share of intangible-intensive firms delivered by the model exactly matches what we observe in the data.

New cohorts increase their average intangible share (intangible capital over total capital) by around 5 percentage points both at birth and at age 10 (see Figure 20). Figure 22 shows the increase by age in the level of new cohort's intangible capital. It is clear that the levels of intangibles for each type of firms separately are almost unchanged, while the average level of intangible capital increases because of the composition effect which favors, both at birth and over time, intangible-intensive firms. Finally, Figure 21 shows that the model is able to replicate quite well both the level and the dynamics by age of the change in the intangible share estimated in the data.

The model also replicates the increase in capital productivity of new cohorts after the crisis (see Figure 11). In particular, the mild reduction in revenues (see Figure 23) coupled with the more intense one in capital (Figure 24) gives rise to an increase in capital productivity (Figure 25). Again, both developments are mainly a consequence of a composition effect, since intangible-intensive firms are less capital intensive and more profitable. The higher average TFP at entry of tangible-intensive establishments, though favouring a bigger size for those firms (Figure 26), is not sufficiently strong to counter the fall in capital accumulation.

7 Conclusion

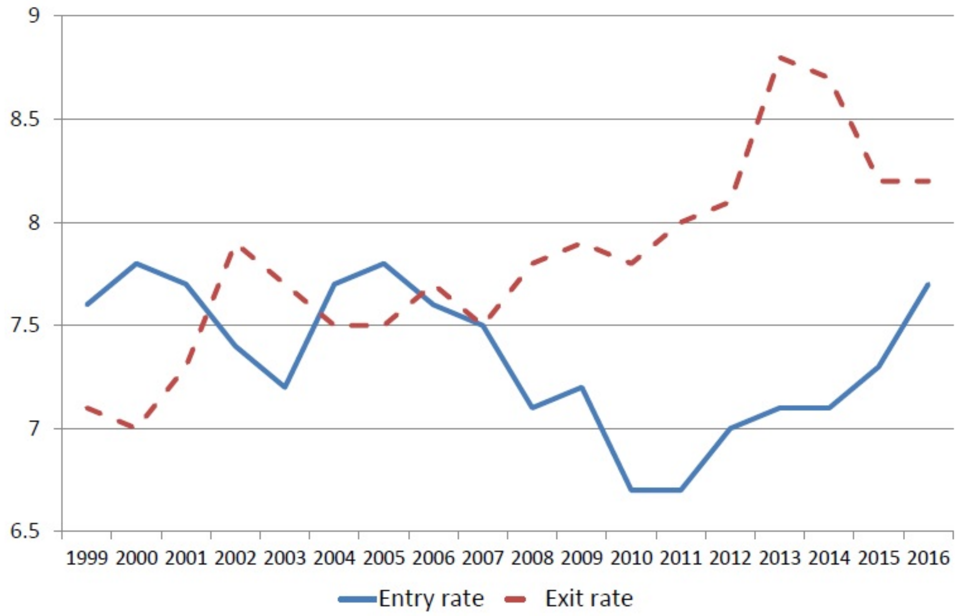
Using the census of Italian incorporated firms we document that producers with an above-the-median share of intangible capital (e.g. in R&D or software) have a higher total capital productivity compared to other firms. Since the differences in TFP among intangible- and tangible-intensive firms are relatively small, these data suggest that higher capital productivity stems from increased efficiency linked to investment in intangibles. We show that intangible-intensive firms suffered less from the financial shock, in terms of their finances, both at entry and exit during the 2007-13 crisis. Furthermore, we find that the intangible intensity and capital productivity of new cohorts increased during the crisis. We provide evidence of the causal role played by the 2007-8 credit tightening in promoting firm selection, both at entry and exit, in a natural experiment setting. We use a firm dynamics model to illustrate how intangible-intensive firms can be more resilient to a financial shock. In our model, these firms need less capital and lower leverage to survive, thanks to the higher efficiency of intangible capital. On the contrary, tangible-intensive firms need more capital to operate, have higher leverage and lower profitability. They are therefore not able to absorb a sharp increase in their financing costs as well. Only very productive tangible-intensive producers are able to enter the market after the financial shock. This causes a sharp reduction in the number of tangible-intensive firms operating in the market. Overall, new cohorts of firms benefit from a composition effect, whereas entrants are skewed in favor of intangible-intensive and more efficient producers. Although the effect of the financial shock on the aggregate productive potential of the economy

[11] Our objective is to uncover the sources of selection that lie behind the change in the *share* of high- versus tangible-intensive firms during the crisis. With this in mind, we do not consider the overall decrease in the entry rate after the crisis, but we normalize the mass of firms both before and after the crisis and concentrate on the share accounted for by each type of firm. Since we are working in partial equilibrium and wages do not adjust, the mass of entrants in the model must decrease sharply to clear the labor market after the shock. A more credible change in entry rates would occur in a model with aggregate uncertainty, as in Clementi and Palazzo (2016).

is negative, since the total number of operating establishments decreases, the positive selection effect on the composition of new cohorts mitigates the negative effect. While our model has no role for endogenous innovation, an increase in the overall intangible intensity of the economy can potentially boost innovative activities and growth as the new cohorts age.

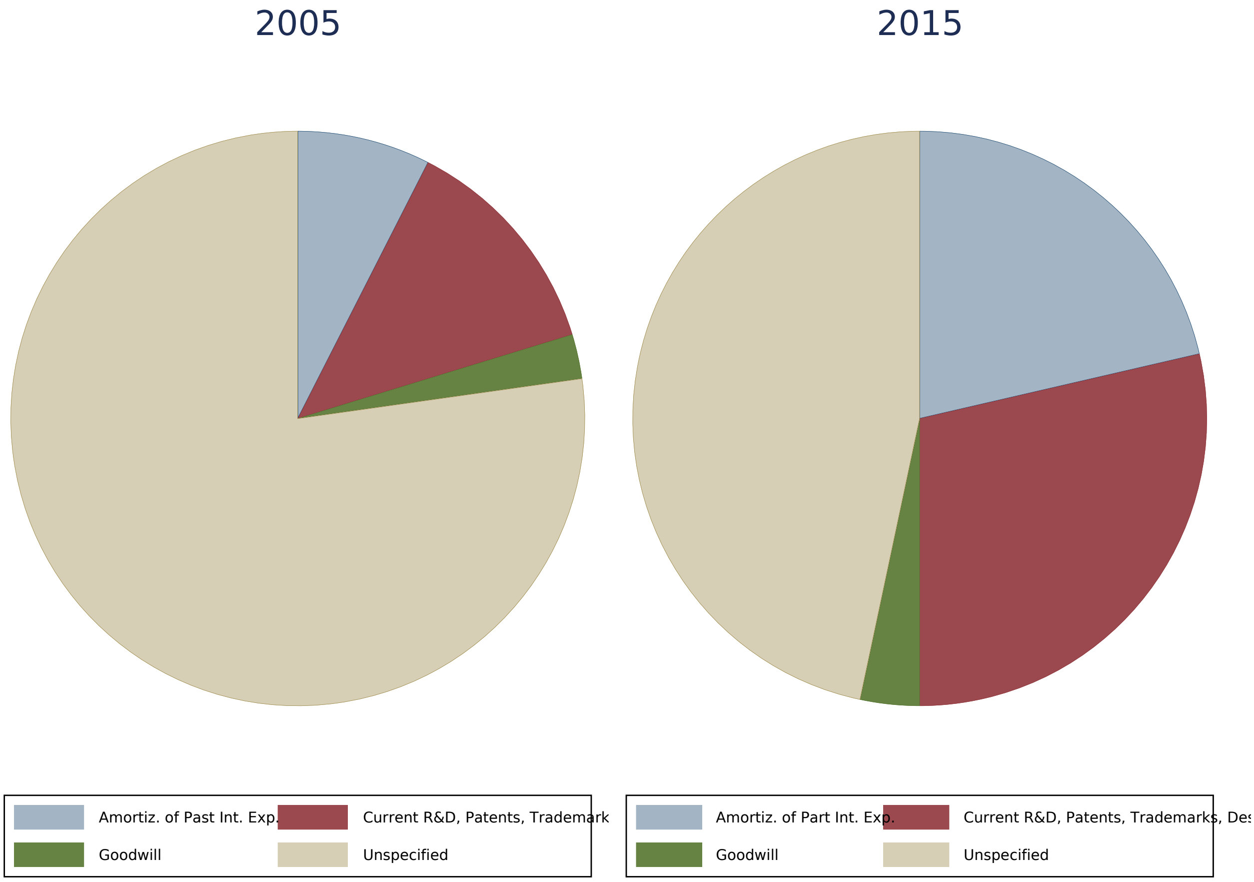
Empirical Figures

Figure 1: Entry and exit rates in Italy



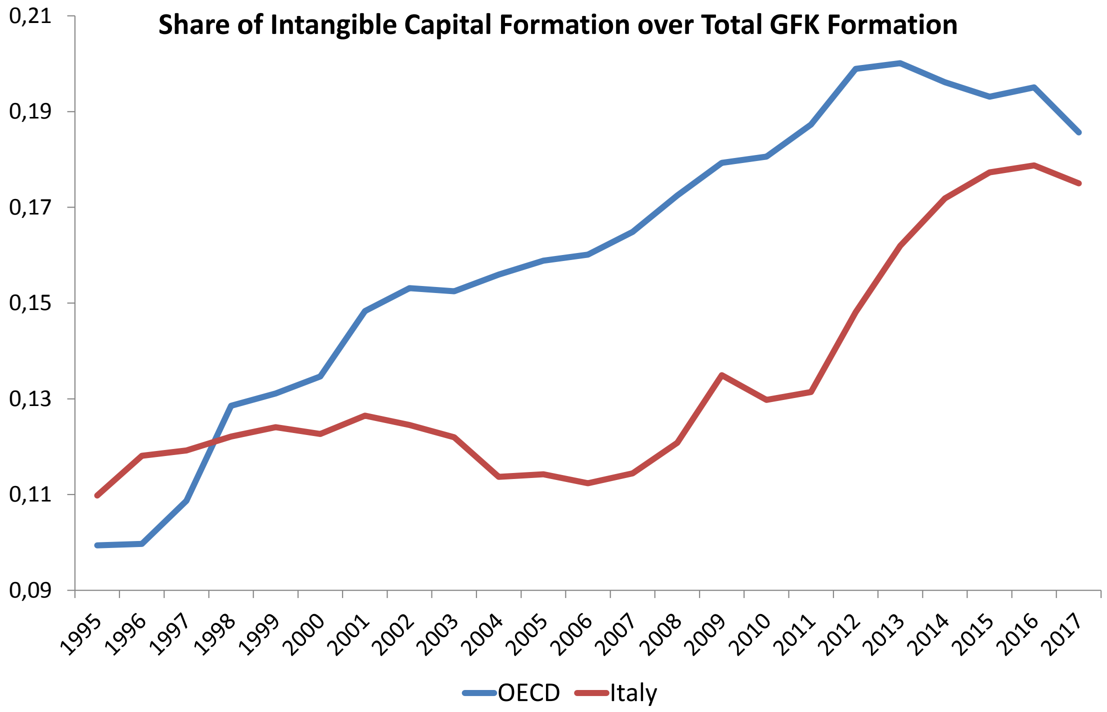
Source: Italian National Statistical Institute (Istat).

Figure 2: Intangible Capital by Type



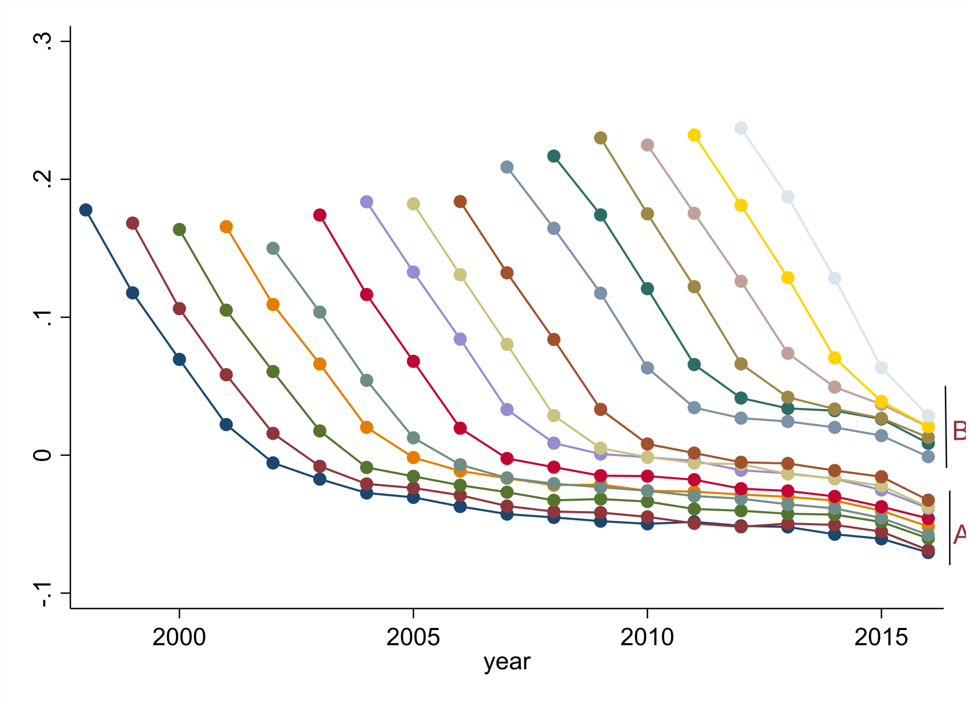
Source: Italian National Statistical Institute (Istat).

Figure 3: Intangible Gross Fixed Capital Formation over Total Gross Fixed Capital Formation



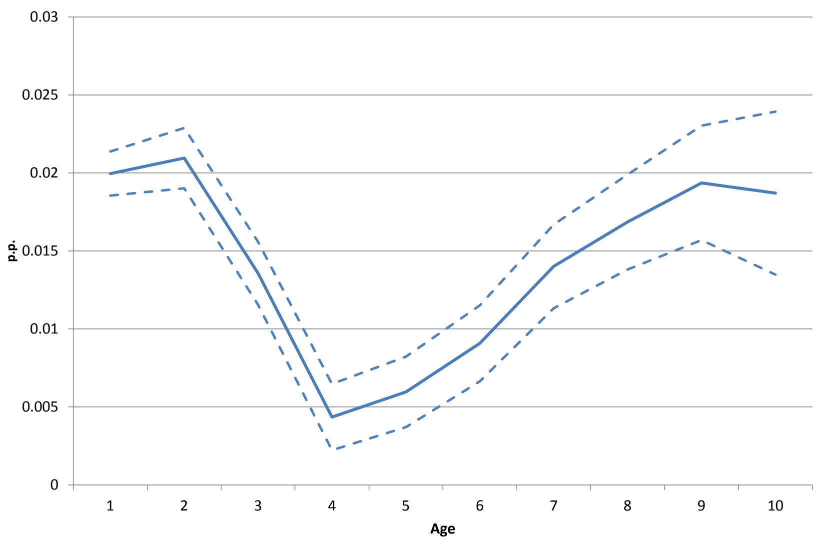
Source: Eurostat.

Figure 4: Intangible capital share, cohort variation



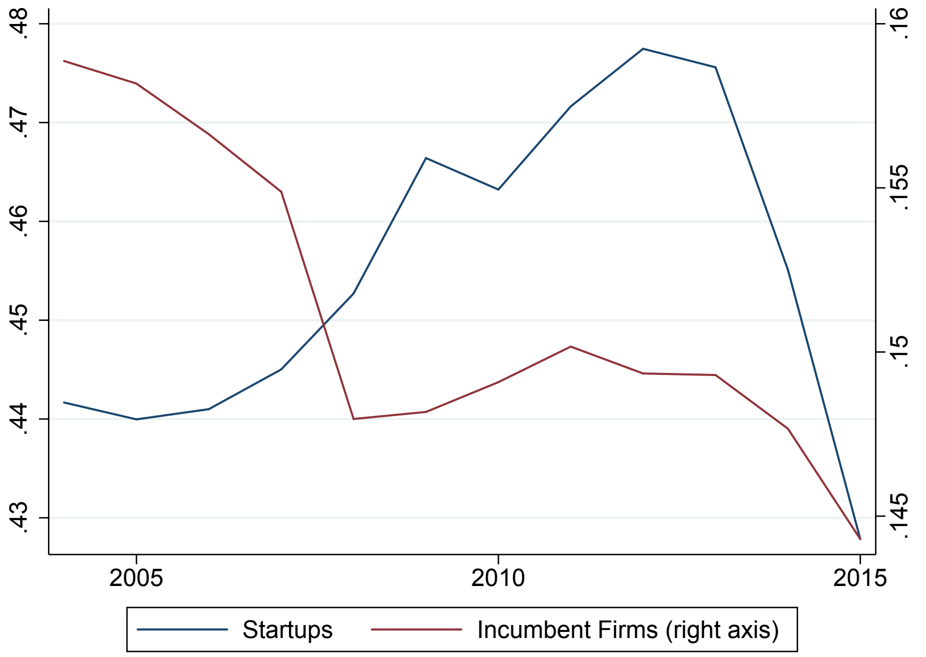
Notes: The figure reports the share of intangible capital over total fixed capital of cohorts born in different years (identified by different colors). 2-digits industry and province fixed effects have been partialled-out.

Figure 5: Intangible capital share, difference between crisis and non-crisis cohorts



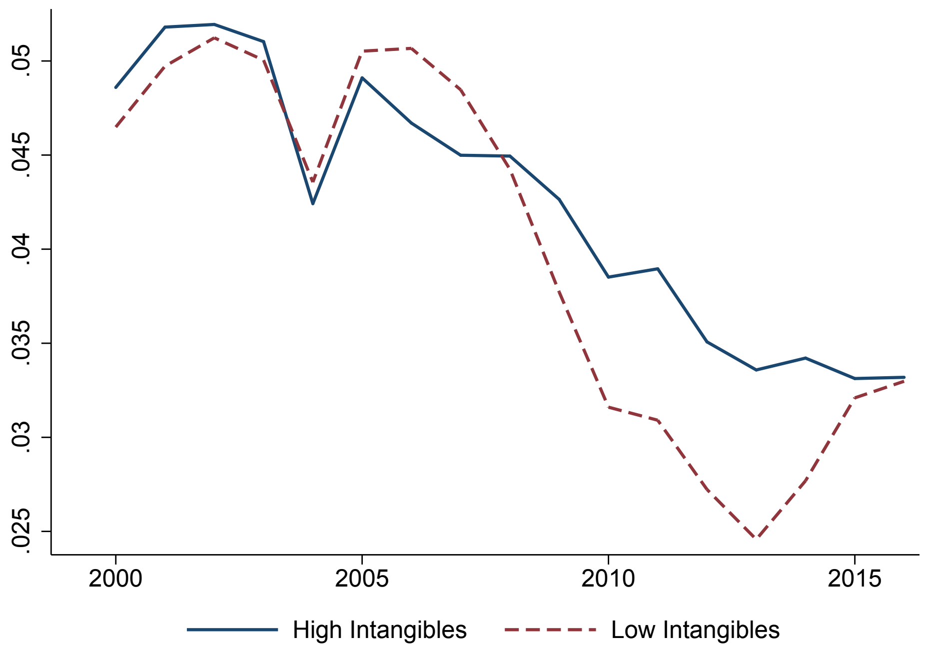
Notes: The figure reports the estimated difference, by age, of the average share of intangible capital over total fixed capital between crisis cohorts (2007-2013) and non-crisis cohorts (1999-2006). 2-digits industry, province, and year fixed effects have been partialled-out.

Figure 6: Intangible intensity of startups and incumbent firms



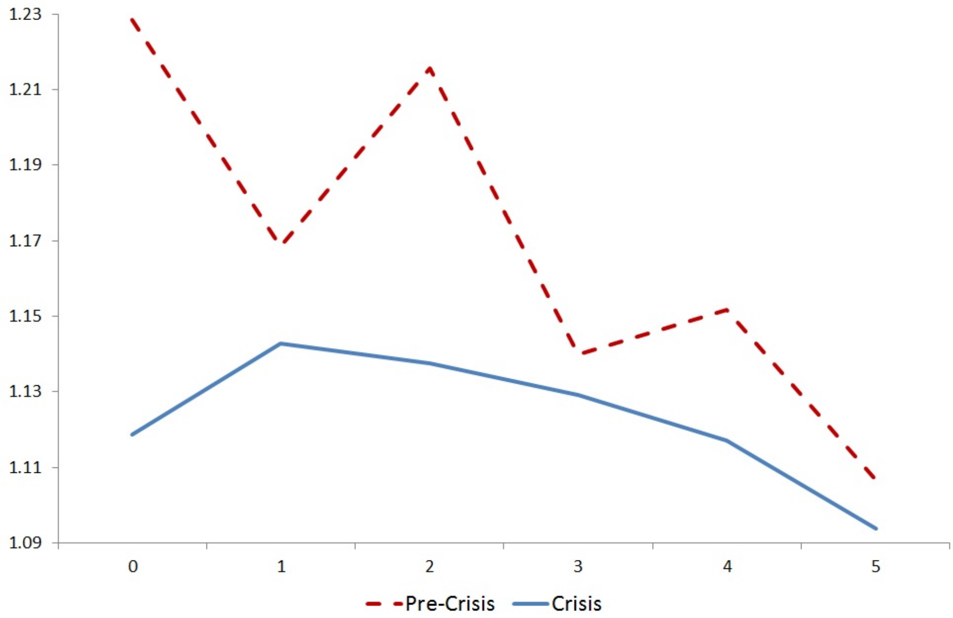
Notes: The figure reports the average share of intangible capital over total fixed capital for startups and incumbent firms.

Figure 7: Entry rates by intangibility of capital at entry



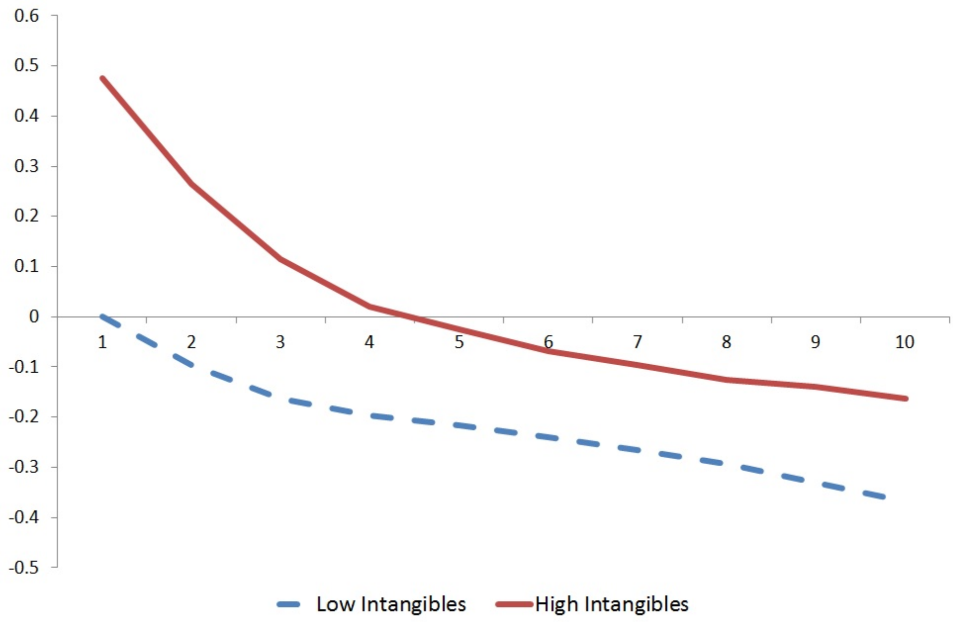
Notes: The figure reports the entry rates of high- and low-intangible firms over time. High intangibility is defined as having a share of intangible over total capital above the median, as measured in the years before the crisis (1999-2006). Entry rates are measured as the ratio between new entrants (either low or high intangible ones) over the lagged total stock of firms (both low and high intangible ones).

Figure 8: Relative risk of exiting: high intangibles VS low intangibles



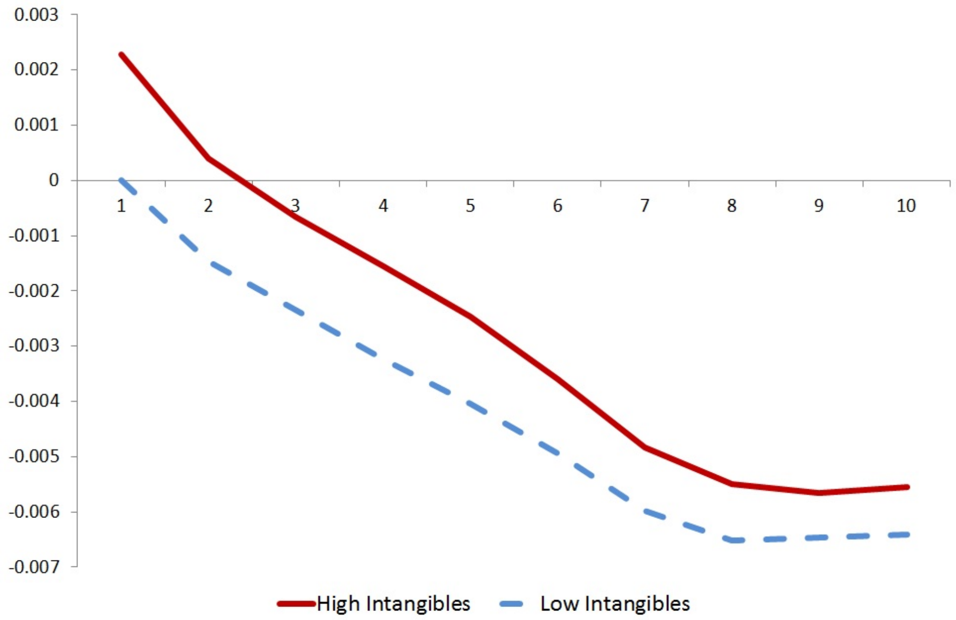
Notes: The figure reports the relative risk of exiting of high- VS low-intangible firms ($Pr(exit|HighIntangible)/Pr(exit|LowIntangible)$) by age, for crisis and pre-crisis cohorts. Crisis cohorts are those born between 2007 and 2013. High intangibility is defined as having a share of intangible over total capital above the median, as measured in the years before the crisis (1999-2006). 2-digits industry, province, and year fixed effects have been partialled-out.

Figure 9: Capital productivity differentials between high and low-intangible firms



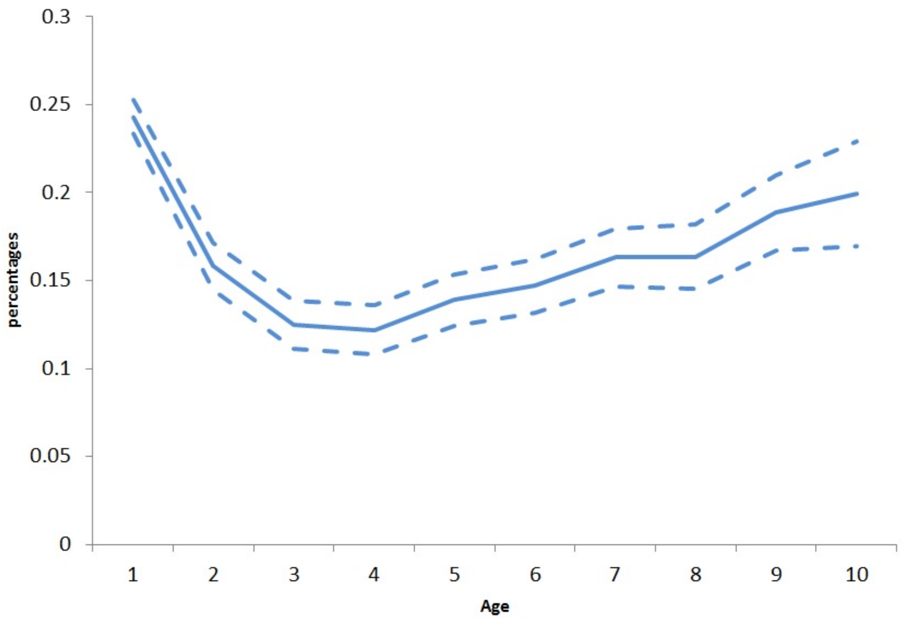
Notes: Low/high intangibility refers to being below/above the median share of intangible over total fixed capital as measured over the period 1999-2006. 2-digits industry, province, and year fixed effects have been partialled-out.

Figure 10: Total factor productivity differentials between high and low-intangible firms



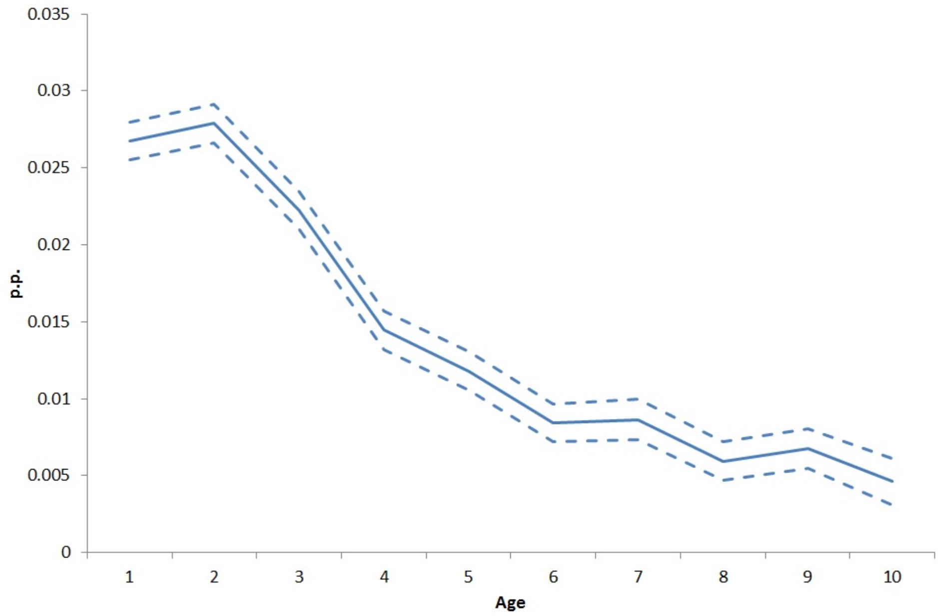
Notes: Low/high intangibility refers to being below/above the median share of intangible over total fixed capital as measured over the period 1999-2006. Total factor productivity is obtained from a Translog production function, using the De Loecker and Warzinsky (2016) estimator. 2-digits industry, province, and year fixed effects have been partialled-out.

Figure 11: Capital productivity differentials by age between crisis and pre-crisis cohorts



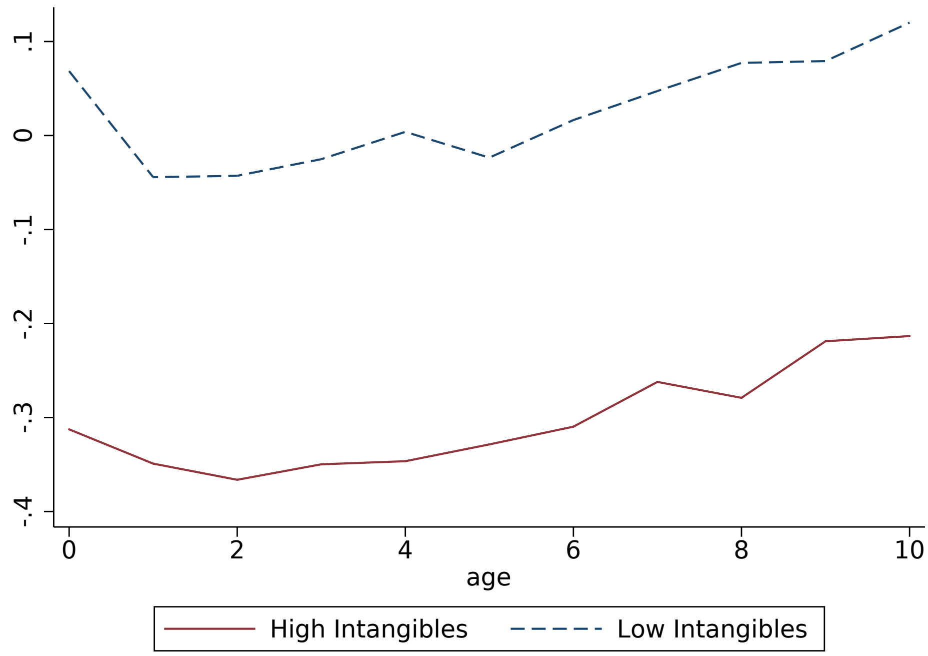
Notes: The figure reports the estimated difference, by age, of the average capital productivity (revenues over total fixed capital) between crisis cohorts (2007-2013) and non-crisis cohorts (1999-2006). 2-digits industry, province, and year fixed effects have been partialled-out.

Figure 12: Total factor productivity differentials by age between crisis and pre-crisis cohorts



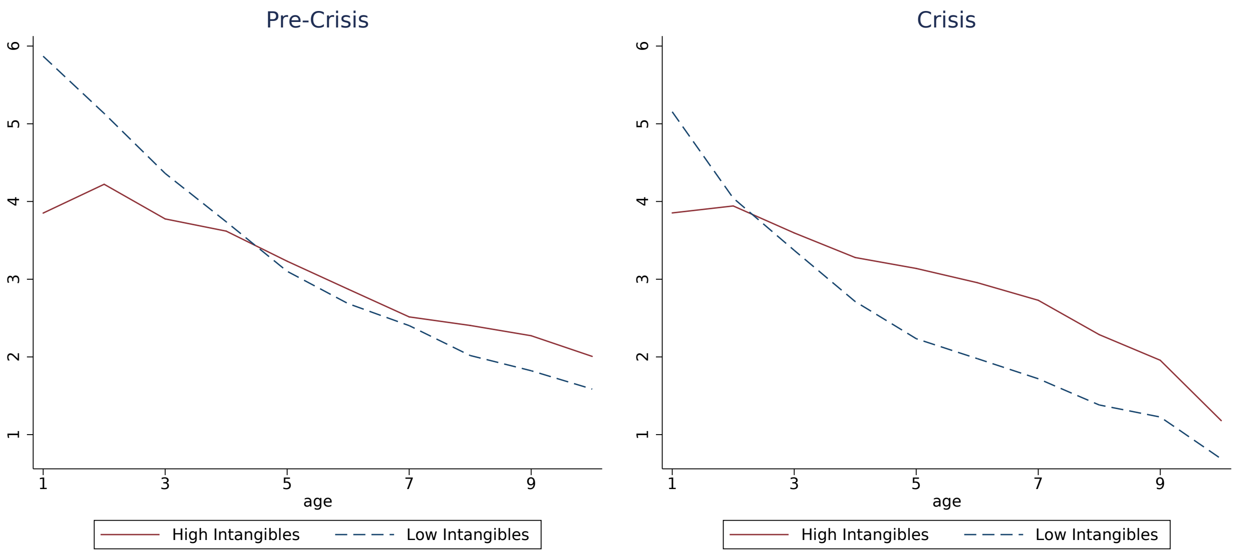
Notes: The figure reports the estimated difference, by age, of the average Total factor productivity (obtained from a Translog production function, using the estimator by De Loecker and Warzinsky 2016) between crisis cohorts (2007-2013) and non-crisis cohorts (1999-2006). 2-digits industry, province, and year fixed effects have been partialled-out.

Figure 13: Capital/labor ratio by age of high- and low-intangible firms



Notes: Low/high intangibility refers to being below/above the median share of intangible over total fixed capital as measured over the period 1999-2006. The figure reports the average capital/labor ratio for high- and low-intangible firms, after partialling out industry-year fixed effects.

Figure 14: Leverage of intangible-intensive and tangible-intensive firms by age - pre-crisis and crisis cohorts



Notes: The figure reports the average leverage of intangible-intensive and tangible-intensive firms by age. Leverage is the residual of $assets/networth$ after partialling out industry-year fixed effects; high- (low-)intangibility is defined as having a higher-(lower-)than-median intangibility of capital at birth.

Figure 15: Effect of interbank exposure on various measures of credit supply tightness

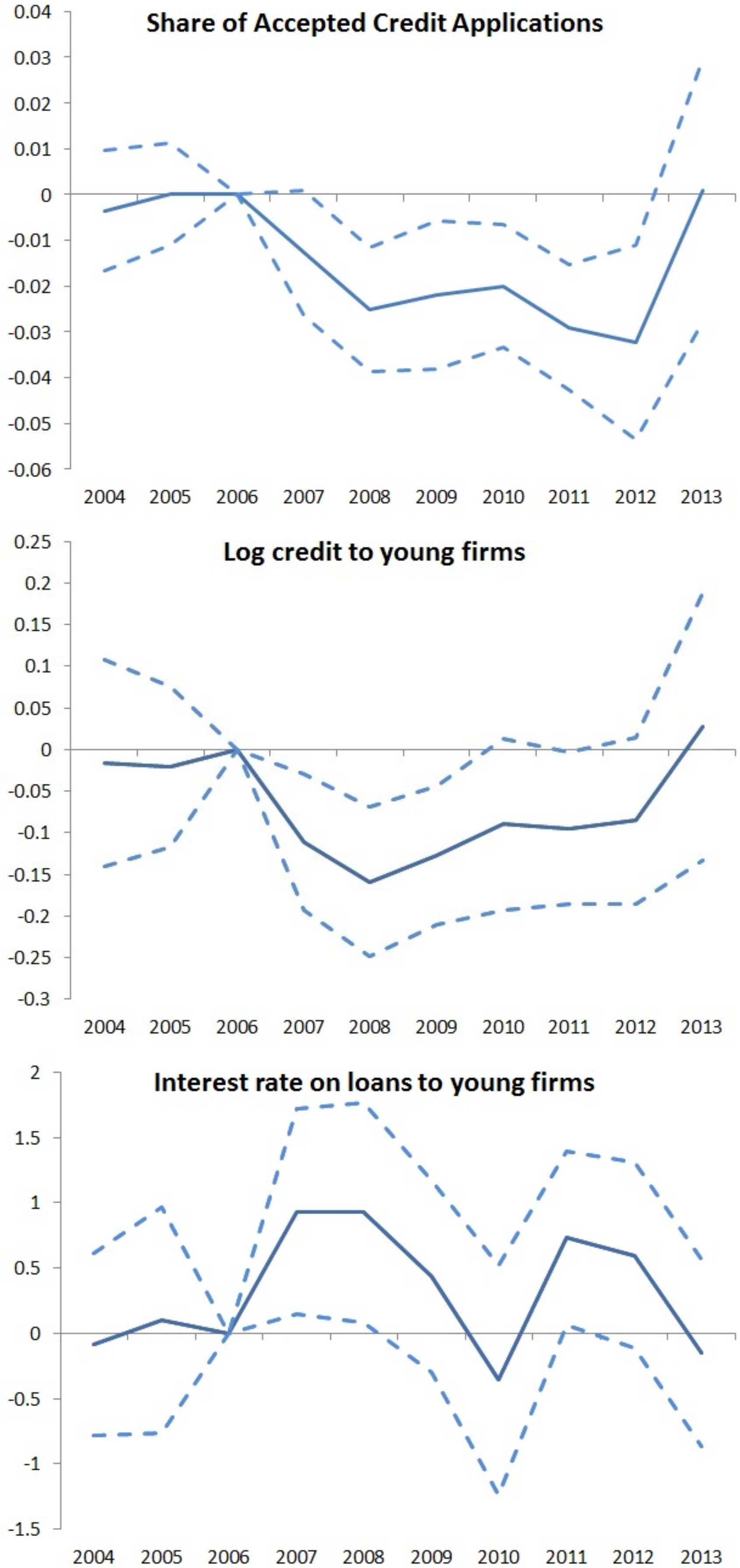
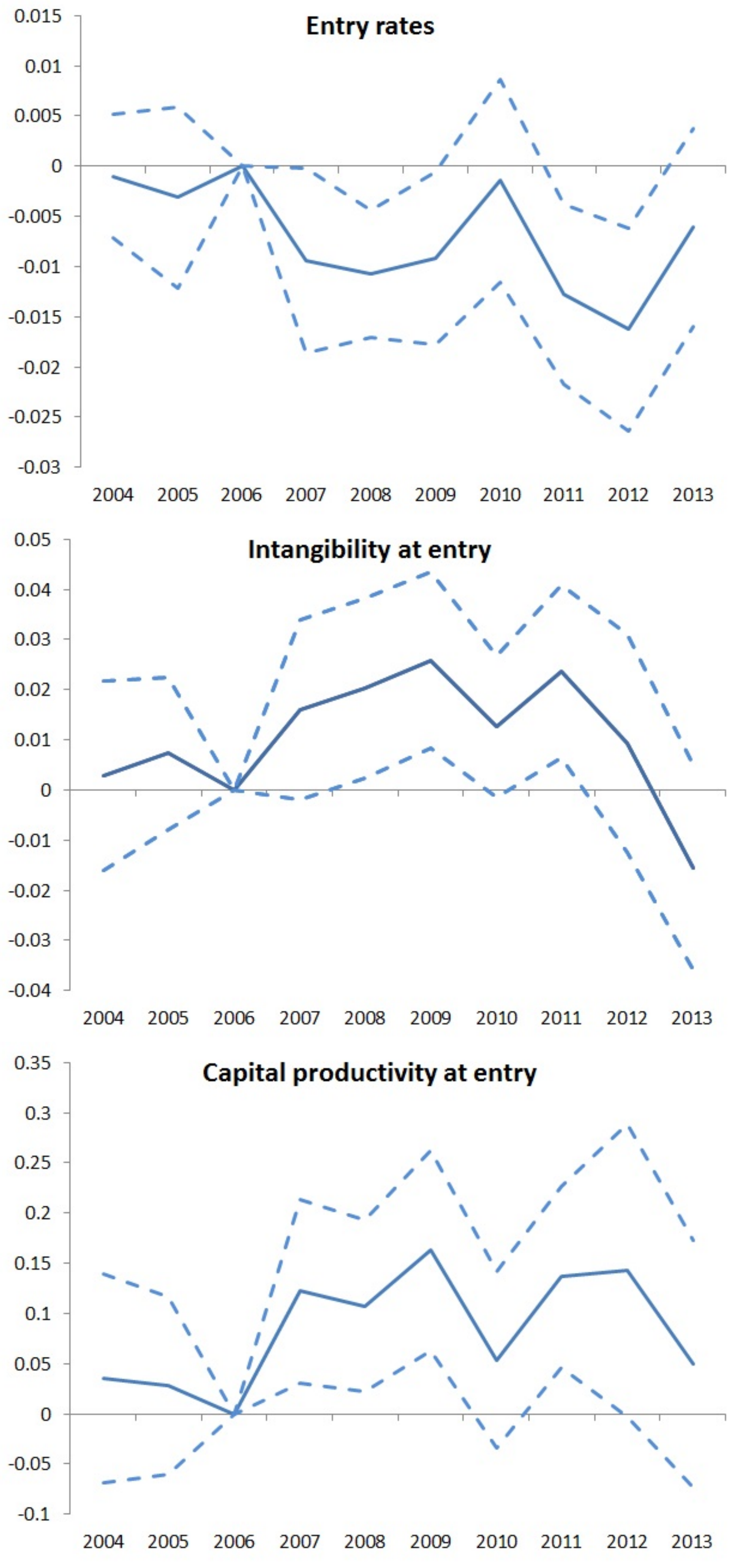


Figure 16: Effect of interbank exposure on firm entry and selection



Model Figures

Figure 17: Exit Rates by Intangible Intensity: initial steady state

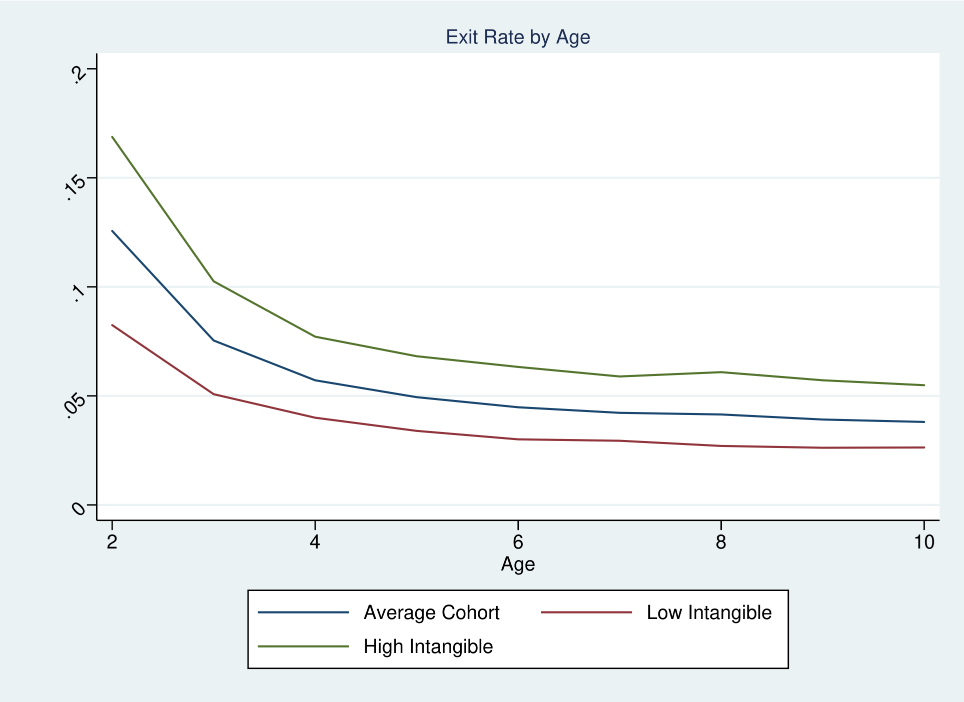
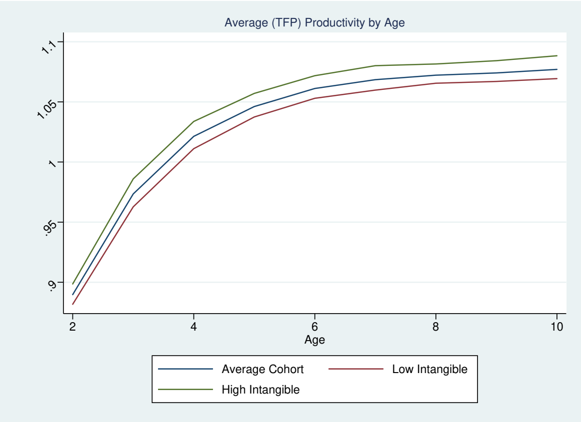


Figure 18: Average TFP

(a) Baseline



(b) Credit Crunch

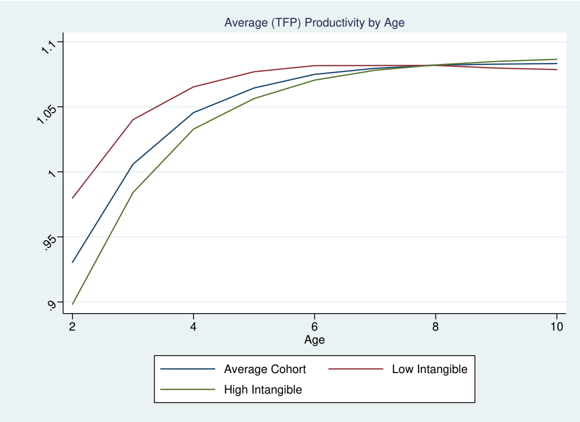
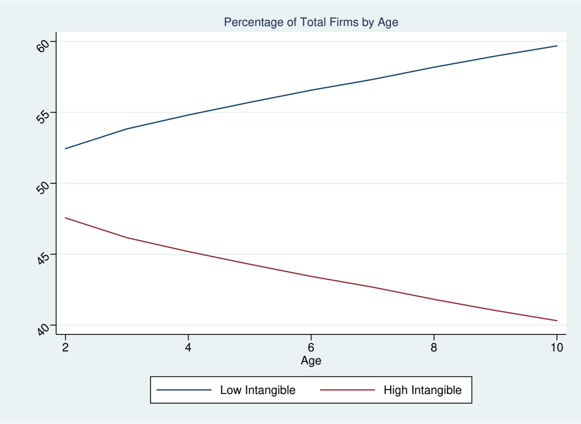


Figure 19: Percentage of firms using either technology

(a) Baseline



(b) Credit Crunch

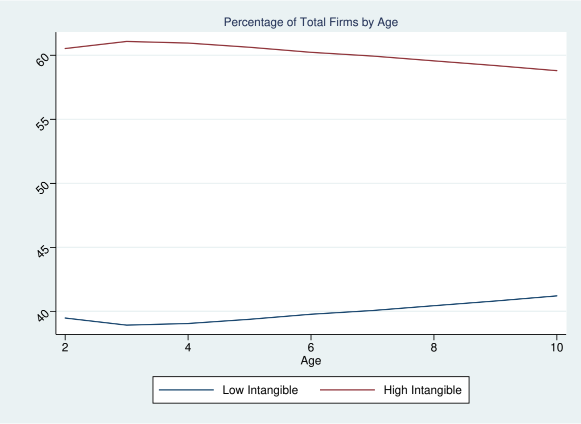
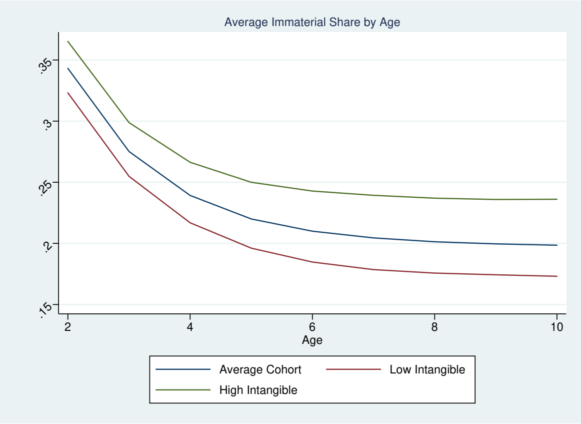


Figure 20: Average Intangible Share

(a) Baseline



(b) Credit Crunch

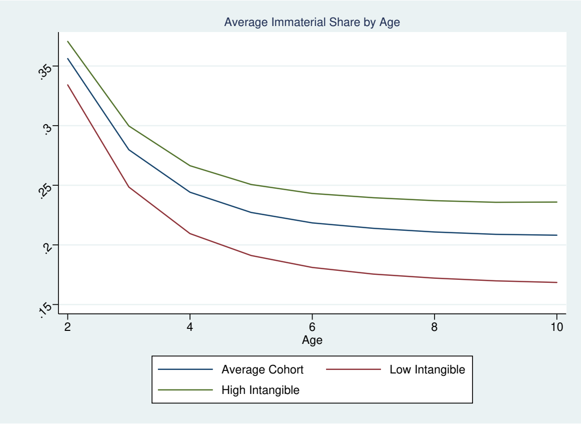


Figure 21: Change pre- vs post-crisis in intangible intensity: Model versus Data

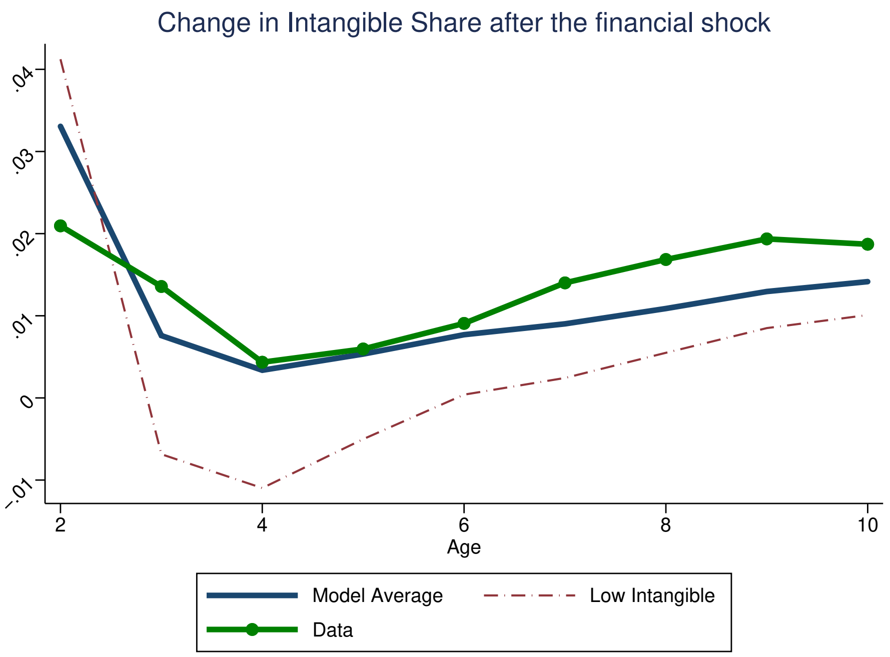


Figure 22: Average Intangible Capital

(a) Baseline

(b) Credit Crunch

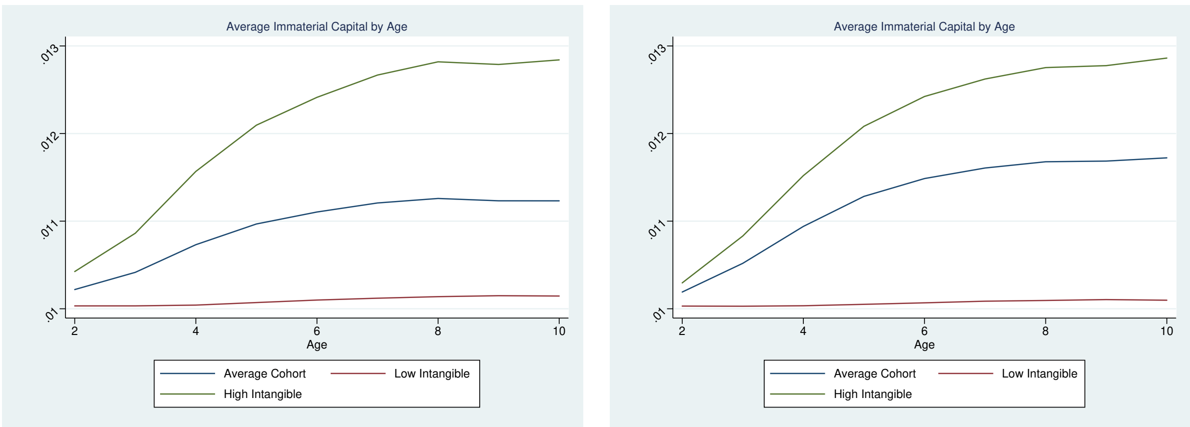
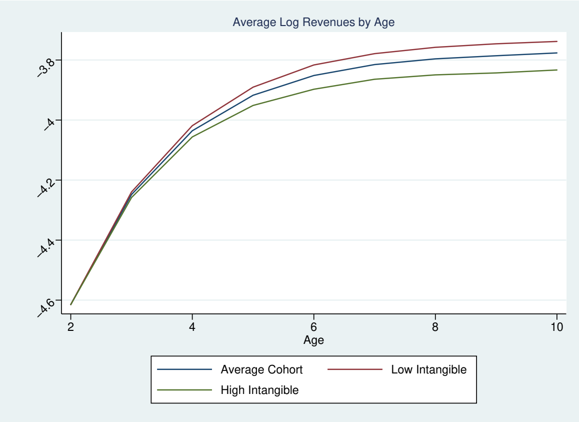


Figure 23: Average Log-Revenues

(a) Baseline



(b) Credit Crunch

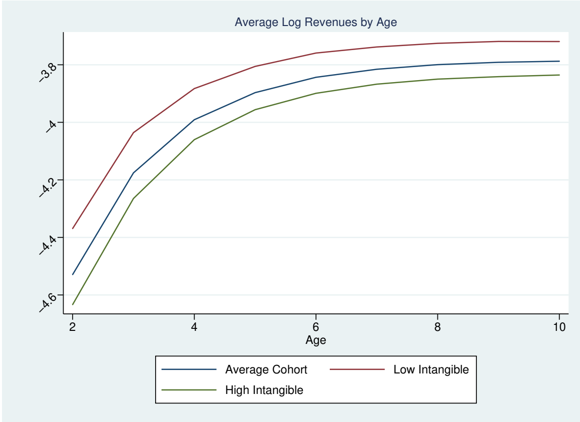
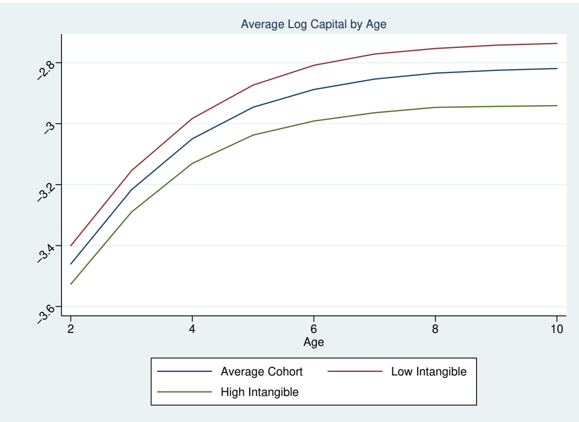


Figure 24: Average Log-Capital

(a) Baseline



(b) Credit Crunch

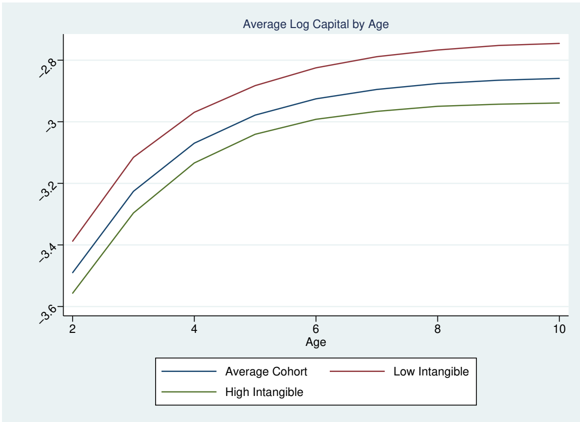
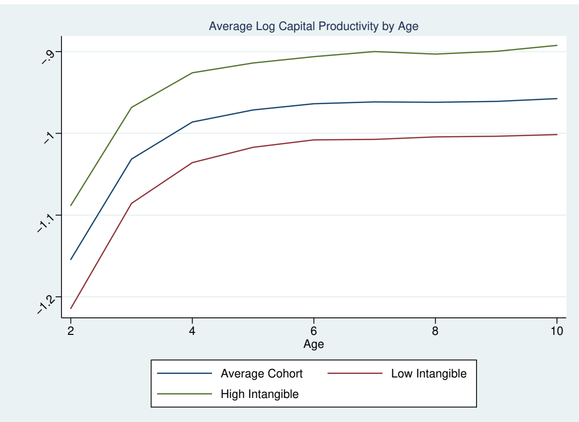


Figure 25: Average Log-Capital Productivity

(a) Baseline



(b) Credit Crunch

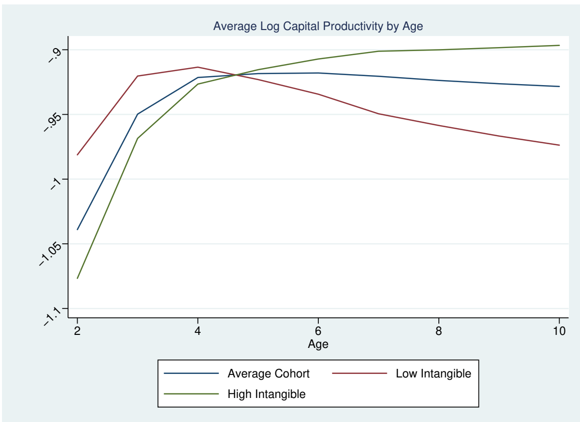
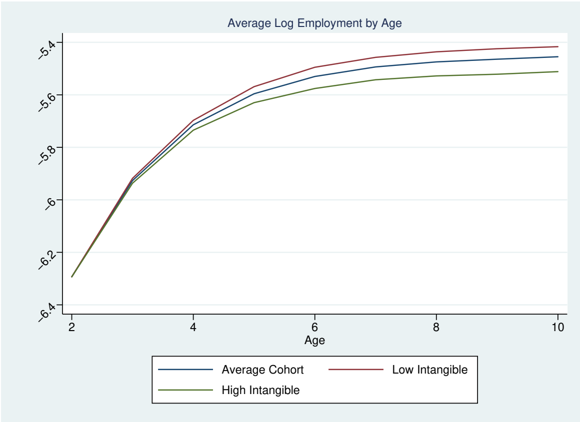


Figure 26: Average Log-Labor

(a) Baseline



(b) Credit Crunch

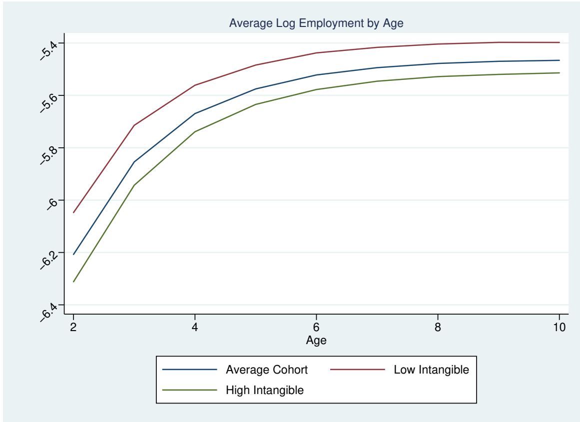


Figure 27: Capital-Labor Ratio by Intangible Intensity

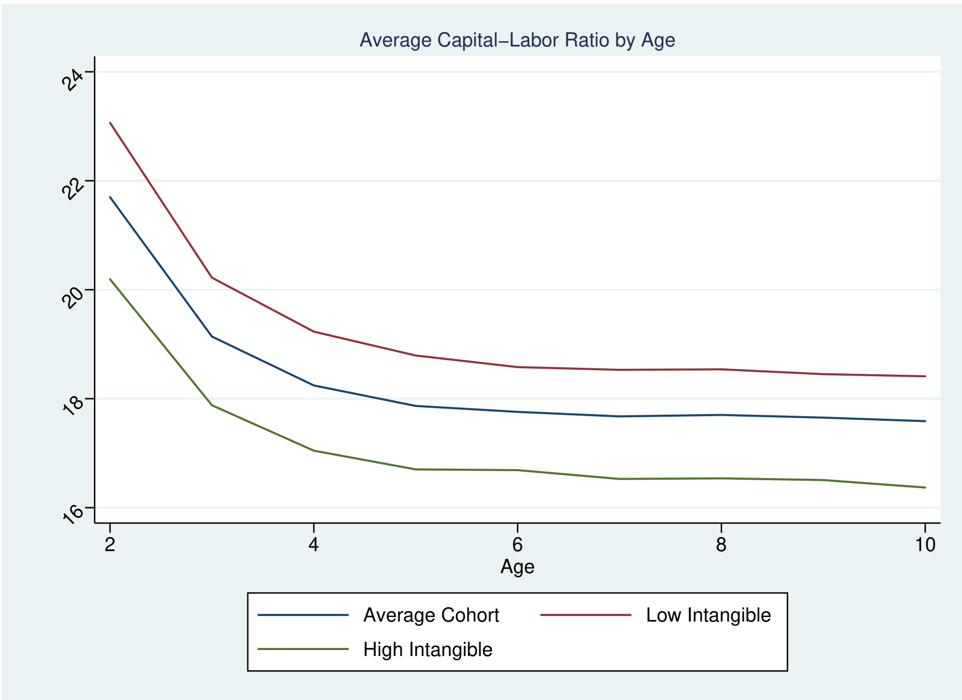
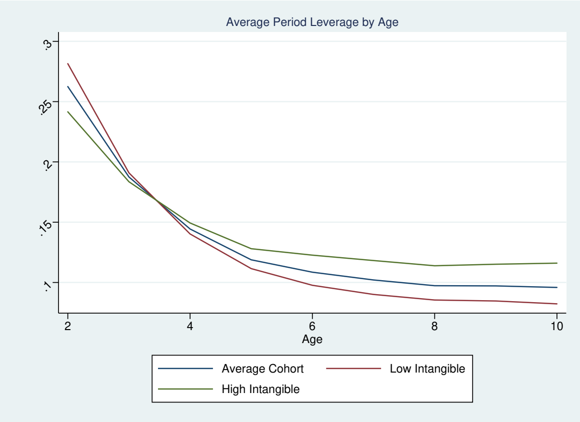
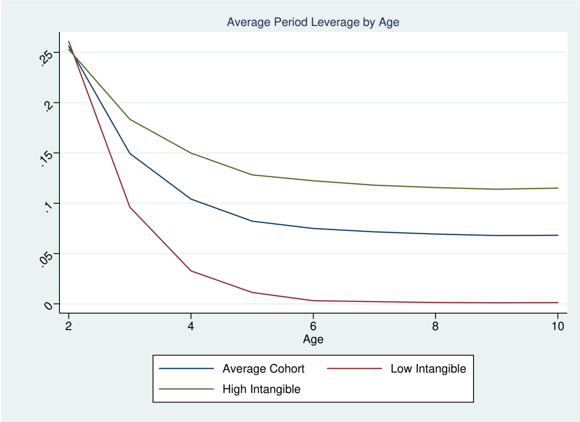


Figure 28: Leverage: External Finance over Total Capital

(a) Baseline



(b) Credit Crunch



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