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Abstract

We study the adoption of different intangible investment strategies in manufacturing firms. Contrary to most of the previous literature, we find such strategies to be highly differentiated. In particular we identify three types of investment behaviour: high and persistent, low and persistent, discontinuous. Using as a reference the capability-based view of the firm, we define and provide support for a set of hypotheses on the determinants of such behaviours. We obtain the following results: first, absorptive capacity led by R&D expenditures is a key competence in sustaining the adoption of an intangible investment strategy, which may be either persistent or discontinuous; second, the implementation of a persistent intangible investment strategy necessarily requires specific investments in the quality of human resources to be made; third, firms with a greater propensity to operate in international markets are more likely to adopt a persistent intangible investment strategy than they are to adopt a discontinuous one; fourth, firms that undertake a growth path that is based on highly uncertain demand segments and high organisational flexibility are likely to adopt a discontinuous intangible investment strategy; and five, the historical intangible asset base represents an important constraint on firms? investment behaviour.

Jelcodes:M21,-

Intangible Asset Dynamics and Firm Behaviour

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Abstract

We study the adoption of different patterns of intangible assets accumulation in manufacturing firms. Contrary to most of the previous literature, we find such patterns to be highly differentiated. In particular, we identify three types of firm behaviour: high and persistent, low and persistent, discontinuous. We link the capability-based view of the firm to theories of assets complementarities and market signalling to explain how firm-specific traits affect such behaviours. We obtain the following results: first, the persistent accumulation of intangible assets is favoured by the internal availability of highly skilled personnel; second, firms with a) large intangible assets base and b) high propensity to exploit complementarities in the asset stocks are more likely to persistently accumulate intangible assets than to discontinuously or never accumulate intangible assets; third, the adoption of quality management standards facilitates the accumulation of intangible assets, especially if this is done discontinuously. This paper adds to the previous literature in two ways: first, it highlights the existence of great heterogeneity in the dynamics of intangible assets accumulation; second, it provides an explanation for such heterogeneity.

Keywords: *intangibles, firm behaviour, asset accumulation, human capital, complementarities, quality standards*

JEL codes: **D22** (Firm Behaviour: Empirical Analysis); **L21** (Business Objectives of the Firm); **L25** (Firm Performance: Size, Diversification, and Scope); **O32** (Management of Technological Innovation and R&D)

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1. Introduction

The role of intangible assets in supporting firm's performance has been widely claimed, in both the academic and policy debate. Differently from the standard "R&D centric" approach to innovation, and in line with more recent trends such as the "system approach" to innovation (Carlsson et al., 2002) and the "open-innovation mode" (Chesbrough, 2003), this literature has stressed the importance of additional factors as key drivers of firm's innovation, such as designs, software, blueprints, technology licences, and trademarks. These resources are generally referred to as intangible assets and their contribution has been analysed with respect to different dimensions of economic activity. At the macro-level, for instance, growth-accounting exercises have shown that intangible assets explain a larger share of labour-productivity growth than tangible assets in a number of countries (Corrado et al., 2005, 2009; Fukao et al., 2009; Marrano et al., 2009; Borgo et al., 2013). At the micro-level a number of studies have pointed to the existence of a positive link between intangible assets and firm's productivity (Marrocu et al., 2012; O'Mahony and Vecchi, 2009; Bartel, 2007; Bontempi and Mairesse, 2008; Jiménez-Rodríguez, 2012; Hall et al., 2013; Battisti et al., 2014), market value (Hall et al., 2005; Greenhalgh and Rogers, 2006; Sandner and Block, 2011; Hulten and Hao, 2008), and export (Delgado-Gómez and Ramírez-Alesón, 2004). Intangible assets have also become an important focus of policy initiatives within the European Union.[1]

Although the literature on intangible assets is extensive, to date, there has been little empirical work on the determinants of intangible asset accumulation at the firm level. One of the few exceptions is a recent paper by Arrighetti et al. (2014), which uses balance sheet and survey data on Italy to study firms' propensity to invest in intangible resources. Interestingly, this work finds a quasi-Pareto distribution in firms' propensity to invest, with few firms making substantial investments and many others investing almost nothing (i.e., displaying high heterogeneity). In addition, the results show firm-specific features such as size, human capital and the historical intangible asset base to play a major role in explaining the propensity to invest.

Along these lines, one aspect that has still received relatively little attention concerns the

[1] See the recent series of well-known Framework Research Projects like INNODRIVE, COINVEST, INDICER, and IAREG.

dynamics underlying intangible assets accumulation at the firm level. In particular, no study has so far taken into consideration the existence of different patterns of accumulation within firms. In theory, intangible assets are often described as resources whose process of accumulation is highly persistent (see Teece, 1986; Dierickx and Cool, 1989; Knott et al., 2003), so that the main differentiation has been made between those who invest and those who do not invest in these assets. Relatively little attention instead has been paid on the specific features of the pattern of intangible investment. This contrasts remarkably with some recent trends in the economics of innovation literature, where various authors began to compare alternative models of firm's investment – see for instance the contributions on persistent vs. volatile R&D expenses (Blazenko et al., 2012; Cuervo-Cazurra and Un, 2009), episodic vs. continuous organizational change (Romanelli and Tushmann, 1994; Wischnevsky and Damanpour, 2006) as well as innovation persistence (Antonelli et al., 2012, 2013).

The relevance of studying the diversity of intangible assets accumulation dynamics emerges also from the data. In fact, a careful examination of firms' behaviour (see Section 2) reveals that, if adequately investigated, the pattern of intangible assets accumulation may be much more differentiated than typically thought. When a sufficiently long time span is considered, distinct typologies of firm behaviour begin to emerge. In our dataset, in particular, there are firms (approximately 55% of the sample) that exhibit highly persistent behaviour characterised by either very high or very low intangible capital intensity. However, there exist others (45% of the sample) that exhibit substantial discontinuities. The latter, in particular, show alternate periods of positive investments with periods of relative stasis for an overall pattern of accumulation that is highly volatile.

Based on this evidence, the present paper investigates the factors that may explain the existence of these different types of accumulation dynamics among firms. Given that intangible assets and, more generally, knowledge assets are usually described as resources that exhibit fairly persistent accumulation dynamics, how can we explain the degree of volatility that distinguishes a large proportion of firms? What are the factors that may explain the evolution of these distinct patterns of intangible assets accumulation over time? These are the main questions addressed in the remaining sections of the paper.

In our view these differences in firm behaviour can be explained by combining three distinct streams of literature. The first one is the literature on firm's learning and capabilities (Penrose, 1959; Teece, 1980; Nelson and Winter, 1982; Barney, 1991; Teetce et al., 1997; Dosi et al., 2000), which focuses on the firm-specific resources that are necessary for intangible assets to be accumulated. The second one is the literature on technological complementarities (Teece, 1986), which suggests the possibility of lock-in behaviours and persistent heterogeneity in the process of intangible assets accumulation. The third one is the literature on market signalling (Spence, 1973), which stresses the need to complement strategies of intangible assets accumulation with instruments aimed at reducing information asymmetries between sellers and buyers (e.g., quality management standards).

Given this broad theoretical framework, we define and provide support for a set of hypotheses concerning the determinants of distinct patterns of intangible assets accumulation. In particular, we focus on four main variables: (i) human capital; (ii) historical intangible asset base; (iii) asset complementarity; and (iv) quality management standards. For each of these variables we discuss the impact on the probability that a firm adopts a specific pattern of accumulation. Firms are classified according to their accumulation profile using a rank-based algorithmic procedure. The theoretical hypotheses are tested on a rich dataset on Italian manufacturing firms.

Overall, we obtain three main results: first of all, we find that firm's human capital is a key resource in favouring the accumulation of intangible assets, especially if this is done persistently; secondly, we find that firms with a) larger intangible asset base and b) greater propensity to exploit assets complementarities have greater probability to persistently accumulate intangible assets than to discontinuously or never accumulate intangible assets; finally, we find that the adoption of quality management standards facilitates the choice to accumulate intangible assets, especially if this is done discontinuously. With these results we contribute to the present literature on intangible assets in two ways: first, we highlight the existence of great heterogeneity in the dynamics of intangible assets accumulation; second, we provide an explanation for such heterogeneity that is based on both firm-specific and technology-related factors.

The paper is organised as follows. Section 2 discusses the evidence concerning the existence of both persistent and discontinuous intangible assets accumulation dynamics. Section 3 presents a brief overview of the literature and introduces our research hypotheses. Section 4 describes the dataset and the procedure of classifying firms. Section 5 discusses the empirical strategy employed in the estimation and presents the main variables included in the analysis. Section 6 presents and discusses the results. Section 7 lists some robustness checks. Finally, Section 8 concludes.

2. Intangible assets dynamics: persistence or volatility?

Intangible assets are typically described as resources that exhibit highly persistent accumulation dynamics. The reason is usually related to the existence of increasing returns in intangible investments due to both fixed costs and complementarities within the asset stock (Teece, 1986; Dierickx and Cool, 1989; Knott et al., 2003). Along these lines, the main strategic problem faced by managers has often been associated with the process through which firms are able to effectively converge towards persistent paths of intangible accumulation, being confident that such convergence can steadily sustain competitive advantages over time.

Although some evidence on the persistence of intangible investments exists (e.g., Arrighetti et al., 2014), data reveal that when one considers sufficiently long time spans, the taxonomy of firms' behaviour is far more differentiated than is usually thought. In particular, firms tend to adopt strategies that vary considerably in terms of the level and volatility of intangible assets, with the latter dimension being particularly relevant for a surprisingly large fraction of firms.

On this respect, Figure 1 presents the relationship between average level and volatility of the ratio of intangible assets over total assets for the sample of Italian manufacturing firms included in our dataset. We call this ratio intangible capital intensity (*ICI*) and compute the volatility ($\sigma(ICI)_i$) as the standard deviation of *n*-years windows of ICI_i^t normalised by the *n*-years average level of ICI_i^t ($\overline{ICI}_i$) – for more details on how volatility is computed, see the Appendix. The value of both intangible and total assets is derived from the firms' disaggregated balance sheets (see Section 4).[2] Panel A reports the observed values for $\overline{ICI}_i$

[2] Notice that the values reported in the firm's balance sheet refer to the stock of intangible assets, and not the flow. Still, since the measure is net of amortization (which is usually five years), we can capture discontinuities in the accumulation process by looking at how the value of the intangible stock changes over

and $\sigma(ICI)_i$ on the vertical and horizontal axes, respectively. Panel B reports the associated kernel density function.[3] In computing these values, we consider a time span of eight years, with t ranging from 2001 to 2008 (i.e., n = 8)

[Figure 1 about here]

At an intuitive level, firms tend to concentrate in three main groups. First, we have the firms belonging to the peak on the left side of Panel B, in coincidence with the combination $\overline{ICI}_i = 0$ and $\sigma(ICI)_i = 0$ (plus some neighbouring points). These are firms that persistently accumulate very little intangible assets.[4] Second, moving rightward, we have a large group of firms belonging to the main peak in Panel B, characterised by positive values of both $\overline{ICI}_i$ and $\sigma(ICI)_i$. These are firms whose intangible assets tend to be low on average but highly volatile. Finally, we have the long tail, which corresponds to firms characterised by a high level of $\overline{ICI}_i$ (> 1%) and a relatively low $\sigma(ICI)_i$ – consider that the mean and median values of $\sigma(ICI)_i$ for the entire sample are 0.77 and 0.68, respectively. These are firms that persistently accumulate a large amount of intangible assets.

Overall, especially in light of the large number of firms that exhibit high volatility, Figure 1 reveals the process of intangible asset accumulation to be fairly different from a plainly flat and stable phenomenon. Alongside differences in the level of investments, the accumulation of intangible assets may also diverge in terms of dynamics. Firms that undertake strategies characterised by highly persistent patterns of accumulation tend in fact to co-exist with firms exhibiting huge discontinuities. The main aim of the remaining parts of the paper is thus to investigate the origin of this heterogeneity. On this issue, a set of hypotheses will be presented in the following section.

time. Obviously, this stock measure tends to reduce the average degree of observed volatility with respect, for instance, to a flow measure. However, this effect should be generalized and does not prevent the possibility to compare the relative stability of the accumulation process across firms.

[3] To facilitate the interpretation of this graphic, we report observations where $\overline{ICI}_i \leq 10$.

[4] Although the combination $\overline{ICI}_i = 0$ and $\sigma(ICI)_i = 0$ appears as a single dot in Panel A, we know that it counts 157 observations, i.e., nearly 13% of the sample. These are firms that for the entire period of 2001-2008 report no investment in intangible assets on their balance sheet.

3. Literature review and hypotheses

The existence of discontinuities in the process of intangible assets accumulation is only apparently unexpected. Previous works have indeed shown that some intangible-related investments such as R&D can be markedly discontinuous over time. Moreover, these works have also shown that a large share of firms tends not to invest at all in this type of asset. Blazenko et al. (2012), for instance, show that in firms with positive investments in R&D for at least 10 years, the volatility of expenditures is very high. At the same time, Cohen et al. (1987) reveal that in large U.S. firms, approximately 25% do not report any formal investment in R&D. Similar results are obtained by Galende and Suarez (1999), Cuervo-Cazurra and Un (2010) and Goodwin and Ahmed (2006) as well. The latter, in particular, use Australian data to show that only a minority of firms (30%) capitalise intangibles and that those which do capitalise the values for the various measures of intellectual capital at the firm level exhibit high variance (on this point, see also Clarke et al., 2011).

Similar results have also been achieved in works inspired by the so-called behavioural theory of the firm. Greve (2003), for example, shows that investment in R&D may be highly volatile and offers a possible interpretation for such a result. This volatility is associated with the finding that R&D expenditures tend to increase when low performance leads to "problematic search" and when excess resources cause "slack search". In this sense, higher performance is associated with less innovation, and higher slack is correlated with higher R&D intensity. In addition, a punctuated equilibrium framework (Tushman and Romanelli, 1985) implies that firms adopt different patterns of immaterial investment over time. Firms are moving from exploitation and low R&D activity during periods of stability to exploration and high R&D activity during phases of change (Mudambi and Swift, 2011).

Furthermore, significant differences emerge even among firms belonging to the same industry. On this issue, Ballester et al. (2003) show that even within very narrowly defined sectors, the differences between firms in capitalised R&D investments are considerable.

In addition to the volatility vs. persistence of R&D investments, several authors have also focused on the more general diversity of firms' innovative dynamics. Virany et al. (1992), Romanelli and Thusmann (1994) and Wischnevsky and Damanpour (2006), for instance, compare organizational transformation that is continuous with organizational transformation that is episodic, discontinuous, and intermittent, and investigate their impact on firm's performance. In a similar fashion, the literature on innovation persistence, see for instance Antonelli et al. (2012; 2013), Baraldi et al. (2014) and Roper and Hewitt-Dundas (2008), study the way in which firms differentiate the patterns of innovative performance depending on both their internal resources and the feedbacks received from the surrounding environment. Along the same lines, Rush et al. (2007) analyse the differences across firms' strategies of technological upgrading, distinguishing among: 'unconscious' firms, i.e., those that are unaware about the need for technological change; 'reactive' firms, i.e., those that respond to episodic challenges coming from the competitive environment; and 'strategic' firms, i.e., those that have a well-developed sense of the need for technological change and adopt a strategic approach to the process of continuous innovation. The latter contribution also emphasizes the relevance of detecting firms' behavioural archetypes for the design of policy initiatives.

Differently from this literature, most of the contributions on intangible assets (of which R&D investments are only a fraction) have tended to neglect the issue of heterogeneity in the patterns of accumulation. Several authors have focused on the relative effect of intangible assets on economic performance (Marrocu et al., 2012; Bontempi and Mairesse, 2008; Corrado et al., 2009; Hall et al., 2013; Battistini et al., 2014). Recently, some works have also investigated the firm-level determinants of intangible assets, with a specific focus on the levels of investment (Arrighetti et al., 2014). Meanwhile, contributions concerning the factors influencing the dynamics of intangible assets accumulation are relatively rare.

Motivated by this research void, our main aim in the present paper is to study the diversity of the patterns of intangible assets accumulation. In developing our interpretative framework we build on the capability-based view of the firm and extend it with arguments from the theories of technological complementarities and market signalling. The capability-based view helps us to identify the internal resources that firms need before intangible assets can be accumulated (either persistently or discontinuously). We extend this approach by arguing that, in addition to capabilities, some other features of technological assets can affect firm behaviour, such as the existence of complementarities. The latter can indeed lock firms into given patterns of accumulation and lead to persistent behavioural heterogeneity. Finally, we add an argument derived from the theory of market signalling according to which the propensity to accumulate intangible assets depends on the adoption of complementary management tools that help firms to signal their market value.

On this basis, we identify four variables on which we focus: i) human capital; ii) historical intangible asset base; iii) technological complementarities; and iv) quality management standards. The role of these variables in the firm's decision to adopt a specific pattern of intangible asset accumulation as opposed to another will be analysed separately.

3.1 Human capital

Among the several types of internal resources that have been deemed to facilitate the strategic accumulation of intangible assets, one that has received particular attention in the literature is human capital. Several authors have indeed suggested that the quality of a firm's employees is a basic condition both for generating intangible assets and their economic exploitation (Abramovitz and David, 2000; Galor and Moav, 2004). In this framework, human capital is made up of not only the formal education received by the workforce before hiring but also formal and informal on-the-job training (Barney, 1991; Nerdrum and Erikson, 2001). It represents the collection of skills and abilities that are embedded in the members of the organisation (Bontis and Fitz-enz, 2002) and can be leveraged to expand intangible resources at the firm level. In this sense, therefore, we should expect a firm that is endowed with a highly educated workforce to have the managerial and innovative capabilities necessary to extend its intangible asset base.

At the same time, however, the accumulation and maintenance of human capital is costly for firms. Highly qualified personnel are often paid higher wages and their contribution to firms' activities is difficult to monitor. This creates an incentive for firms with skilled personnel to invest in alternative types of intangible assets, so as to improve competitive advantages and partially compensate for the costly human resource base. In this sense, firms with high human capital will have not only the capabilities but also the need to accumulate intangible assets. Whether such accumulation process is persistent or discontinuous is difficult to say in theory and is mainly an empirical question.

On this basis, the first hypothesis that we put forward is the following:

Hypothesis 1 – *A firm with more human capital is more likely to accumulate intangibles assets, either persistently or discontinuously.*

3.2 Intangible asset base

In addition to human capital, another internal resource that is likely to affect the firm's propensity to accumulate intangible assets is the historical intangible asset base, i.e., the stock of previously accumulated intangible assets. In this respect, several features of the process of intangible asset accumulation may be important, especially in differentiating persistent and discontinuous firms.

First of all intangible assets consist of knowledge, which is cumulative by nature. Within the context of the capability-based view, for instance, Knott et al. (2003) suggest the existence of economies of scale, i.e., asset mass efficiencies, in the generation of the intangible assets from the existing asset stock. According to the original definition of Dierickx and Cool (1989), asset mass efficiencies imply the existence of decreasing marginal costs in assets accumulation, i.e., adding increments to an existing asset stock is facilitated by possessing high levels of that stock. This notion also implies that adopting a persistent intangible investment strategy starting from low or discontinuous initial levels may be difficult, because no critical mass is achieved. The combination of these two factors means that, if anything, we should expect firms making larger (smaller) investment in the past to make larger (smaller) and relatively more (less) persistent investment in the future.

Moving from the structural characteristics of intangible assets to the specific features of firm's behaviour, a similar argument for the existence of a positive relationship between the size of the intangible asset base and the persistence of the accumulation process can be formulated by relying on the idea of organisational learning (see Dosi et al., 2006). In a nutshell, the idea of organisational learning suggests that when a firm adjusts its internal organisation to (a) search the knowledge landscape and (b) invest in a particular type of asset, the firm learns a set of capabilities. These capabilities are likely to generate a relative advantage in pursuing investments in similar and related assets compared to competitors that do not invest in the first place. Consequently, a larger set of intangible resources accumulated in the firm at any given point in time indicates a lower cost of each additional investment and thus a stronger propensity to make large and frequent investment.

Based on these arguments and linking the high frequency of investment to a relatively persistent pattern of accumulation, our second hypothesis is thus as follows:

Hypothesis 2 – *A firm with a large intangible asset base is more likely to persistently accumulate intangible assets than to discontinuously or never accumulate intangible assets.*

3.3 Complementarities

Along with a firm's human capital and intangible assets base, another factor that can certainly differentiate the pattern of intangible assets accumulation is the existence of asset complementarities. As argued by Amit and Schomemaker (1993) asset complementarities refer to situation in which the value of an asset's relative magnitude may increase with an increase in the relative magnitude of other assets. An example is Teece's (1986) notion of co-specialized assets, i.e., those for which there is a bilateral dependence in application. For instance, computer hardware typically requires specialized software both for the operating system and for the applications. Investing in one specialized asset without simultaneously investing in the other makes the firms worse-off than investing in neither of the assets in the first place.

With particular reference to intangible assets, Knott et al. (2003) recognize asset complementarities, or as they call it, interconnectedness of the asset stocks, as a key feature of the process of intangible assets accumulation. A similar view is expressed also by Levinthal (1997), Levinthal and Warglien (1999) and Rivkin (2000), which focus on complementarities among distinct organizational processes. Dierickx and Cool (1989), finally, argue that asset complementarity is indeed one of the main factors that contribute to reduce the imitability of a firm's intangible stock.

The existence of asset complementarities has direct impact on the process of intangible asset accumulation. Since complementarities exist both across stock levels and across time, firms that decide to invest in assets that exhibit complementarities will tend to be locked into an accumulation path that requires frequent and repeated investments. On the contrary, firms that have a lower propensity to exploit complementarities will more free to undertake discontinuous and episodic investments during the accumulation process. As a consequence, depending on the technological features of the initial intangible base, different patterns of intangible assets accumulation may emerge.

On this basis, the third hypothesis that we put forward is the following:

Hypothesis 3 – *A firm that exploits asset complementarities is more likely to persistently accumulate intangible assets than to discontinuously or never accumulate intangible assets.*

3.4 Quality standards

Finally, moving from the firm's capabilities and assets' technological features to the nature of market interactions, a factor that can produce a clear impact on process of intangible assets accumulation is the adoption of quality management standards. In this respect, Terlaak and King (2006) rely on Spence's (1973) theory of market signalling to argue that quality management standard (e.g. ISO) act a primary instrument that firms use for signalling quality of processes/products to their costumers. In their view the usefulness of such tools is greater in contexts where the firm's internal characteristics are more difficult to observe and evaluate. In these cases, in fact, the information asymmetries between buyers and sellers are particularly severe and quality standards can help solving the problem. In support of this hypothesis Terlaak and King's (2006) find that the positive impact of quality management standards on firm performance is larger in industries where firm attributes are more intangible.[5]

Based on this argument, we suggest that the presence of quality management standards can impact on the process of intangible assets accumulation. Firms with quality management standards will be more inclined to accumulate intangible assets, because they are less worried about the impact that a larger intangible asset base could have on the external perception of their attributes. On the contrary, firms without quality management standards will be less inclined to do so, because for them an increased intangible capital intensity is an expenditure that is unequally evaluated by the market. Obviously, it is possible that such relationship holds only up to a certain threshold of the intangible stock

[5] On the difficulty of market valuation of intangibles see also Hall and Oriani (2006) and Bloch (2009).

and after that point other factors play a role in signalling the firm's quality, for instance reputation. Whether this is effectively the case or not it is mainly an empirical question.

On this basis, our fourth and last hypothesis is thus as follows:

Hypothesis 4 – *A firm with (without) quality management standards is more (less) likely to accumulate intangible assets (either persistently or discontinuously) than a firm without (with) quality management standards.*

4. Data and firm type taxonomy

To test the hypotheses defined in the previous section, we use a joint dataset retrieved from two main sources. The first source is the IX wave of Capitalia's Survey on Manufacturing Firms, which covers the period 2001-2003 and contains qualitative and quantitative information for a large stratified sample of Italian firms. In particular, it contains information on workforce composition and education, R&D expenditures, sales, exports, competitors, quality management standard (e.g., ISO 9000), subcontracting, and process and product innovations. The second source is the AIDA-Bureau van Dick database, which contains all Italian firms' disaggregated balance sheet information for the period 2001-2008. With these two sources combined, the final dataset contains 1,130 observations. The representativeness of the original sample is maintained in terms of firm size and industry.[6]

The measure of intangible assets that we consider in our analysis is the sum of three types of asset that are usually reported on the firm's balance sheet under the item "intangible fixed assets", i.e., "research and advertisement expenditures", "patents" and "licenses". This measure excludes goodwill, whose capitalisation is highly subject to managers' discretion and thus is difficult to interpret. The sum of these three assets is then normalised by each firm's total asset size to compute the firm's intangible capital intensity (*ICI*). At any given point in time, ICI_i^t is a proxy of the stock of intangible assets accumulated by firm *i* in period *t*.

Given this set of data, the first step that we take in our empirical investigation is to

[6] Tables reporting on the sample's representativeness are available from the authors upon request.

classify firms according to their accumulation profile. In doing so, the main difficulty that we encounter is related to a relatively non-well behaved distribution of ICI_i^t. In each year, in fact, this variable takes a value of zero for a large portion of firms in the sample (24% on average). Moreover, as shown in Figure 2 for the year 2008, the distribution of ICI_i^t tends to be very concentrated, with over 75% of the firms investing less than 1% of total assets and the top 10% investing from 2% to 38% of their total assets. An analysis of firms' behaviour based on this type of distribution would inevitably emphasize the difference in levels and undermine the heterogeneity of the accumulation dynamics. Given that the latter is indeed the main focus of the present investigation, we must transform ICI_i^t accordingly.

[Figure 2 about here]

In the literature, two transformation rules are usually employed to smooth the shape of distributions, namely taking logs or computing growth rates. In our case, however, none of these options is viable due to the large share of zeros in the distribution. In alternative, we choose to transform ICI_i^t by taking into consideration ranks. In particular, we follow a three-steps classification procedure. First, for each period t in our 8-year window (2001-2008), we rank firms according to their level of ICI_i^t. We call r^t the variable containing the complete *ICI*-rank of firms at time *t*. We then attribute to each firm *i* the vector $\mathbf{r}_i = (r_i^{2001}, r_i^{2002}, \ldots, r_i^{2008})$, where r_i^t is the *ICI*-rank of firm *i* at time *t*. This vector is composed of integer numbers and describes the accumulation of intangible assets of each firm relative to all the other firms included in the sample. Finally, we run the Ward's linkage algorithm (Ward, 1963) on the set of r^t (for t = 2001, … , 2008) to identify clusters of firm profiles.[7]

Overall, the adoption of a rank-based classification procedure presents both costs and benefits. On the side of costs, it makes the accumulation profile of each firm relatively difficult to interpret because it becomes a function of the decisions taken by all the other firms in the sample. On the side of benefits, it achieves two main objectives: first, it smooths the distance between firms with high intangible capital intensity on the one hand

[7] An alternative solution would be to consider transitions across percentiles. In this respect, however, the analysis based on ranks allows for a thinner classification procedure.

and firms with medium and low intangible capital intensity on the other; and second, it increases the variability of the accumulation dynamics, thus making it possible to identify different types of firm profiles. Overall, especially in light of the data we have, we believe that this type of classification procedure represents a useful solution to investigate the evolution of firm behaviours.

Given this classification procedure, we then proceed to validate the clusters, i.e., to establish the number of clusters that most meaningfully captures the distinct profiles of firm behaviour present in our data. Table 1 reports the results of five distinct cluster validation tests for the number of imposed clusters (k) varying from 3 to 6. The average silhouette width (ASW) index (column 1) is high for both k=3 and k=4 and much smaller for k>4, implying a moderate amount of similarity between the former two groupings. The values of Pearson Gamma (column 2) suggest on the contrary to consider k=4 the most suitable solution, whereas, according to Calinski and Harabasz's index (column 3), the best clustering of the data is with k=3. The results of version 1 of Dunn's index (column 4) are in line with the ASW index, showing k=3 and k=4 to be the two optimal choices. The main goal of this measure is to maximise inter-cluster distances (distance between different clusters) while minimising intra-cluster distances (distance between members of a cluster). Version 2 of Dunn's index is similar but focuses on the concept of average dissimilarity and thus yields a somewhat different result, suggesting that k=3 is the optimal number of clusters (although the value of the index is very similar for k=4). All in all, given that three indexes out of five indicate k=3 to be the most meaningful solution, we adopt the latter as the main reference in the remaining sections of the paper.[8]

[Table 1 about here]

The intuition of the presence of three main typologies of firms (i.e., those that persistently accumulate very little intangible assets; those whose process of accumulation is highly volatile and the level of intangible assets is low on average; and those that persistently accumulate a large amount of intangible assets) appears to be confirmed by the

[8] From a qualitative point of view, the computed indexes suggest that the solution with k=4 is not very different from the one with k=3. The main distinction comes from the fact that when we impose k=4, the algorithm tends to split the cluster of firms with a volatile accumulation profile into two, thus adding little in interpretative terms. This finding reinforces our choice of opting for k=3 rather than k=4.

results of the cluster analysis. On this issue, the box plots in Figure 3 report the distribution of the firms' *ICI*-rank per year and firm cluster while imposing *k*=3. These plots clearly show that every year, the three clusters tend to be distinguished in terms of both the mean and variability of the ranks. In particular, we observe that there exist two groups of firms, those labelled 1 and 3 in the figure, exhibiting a relatively low and high average rank, respectively, together with limited variance and range of variation. Meanwhile, there is one group of firms, labelled 2, characterised by an intermediate average rank combined with large variance and a wide range of variation. When considered together, these results suggest that although ranks are by themselves loose measures that depend heavily on what other firms do, the clusters that we identified do capture part of the behavioural differences existing in the underlying data. As a matter of fact, we observe that whereas for one group of firms (i.e., group 2 in the figure) the actual ranks span the entire possible range, for the two other groups, the variation is fairly limited. This difference may in part also be reflected in the distinct evolution of behaviours over time, with the firms belonging to the first group (i.e., group 2) exhibiting high variability and those belonging to the second (i.e., groups 1 and 3) showing high persistence.

[Figure 3 about here]

Some additional features of the three clusters confirm the existence of important differences in terms of firms' behavioural patterns over time. Table 2 reports some descriptive statistics for the whole sample of firms (column 1) and the computed clusters (columns 2-4), with the last column reporting the results of an F-test on the difference between the cluster means. Similarly to the case reported in Figure 3, clusters tend to distinguish in terms of both the average level and the volatility of *ICI*. On one extreme (column 2) exists a cluster of firms (27% of the sample) that on average exhibit a high level of $\underline{ICI}$ (1.98%) and relatively low volatility (0.54). We call this group High Intangible Firms (HIFs). On the other extreme (column 4), there exists another cluster of similar size (28% of the sample) that on average exhibits a low level of $\underline{ICI}$ (0.01%) and low volatility (0.68). We call this group Low Intangible Firms (LIFs). In the middle exist a large cluster of firms (45% of the sample) that on average exhibit relatively low level of $\underline{ICI}$ (0.41) but high volatility (0.97). We call this group Volatile Intangible Firms (VIFs). Each of these clusters is deemed to represent a specific typology of firm behaviour.

[Table 2 about here]

The remaining statistics reported in Table 2 offer the possibility to derive a better understanding of the specific features of the firms belonging to each cluster (for a detailed description of the variables' meaning see the Appendix). By comparing HIFs and VIFs against LIFs, we can first observe that the former two tend to be on average larger (*SIZE*) than the latter. HIFs have a greater proportion of graduated employees (*UNIDEG*) than both VIFs and LIFs and a higher staff ratio (*STAFFRATIO*) and employee's average education (*AVEDU*). This finding lends support to the idea according to which although both HIFs and VIFs have more skilled personnel than LIFs, HIFs have made more systematic investments in sustaining the quality of their human capital compared to VIFs.

Moving from the analysis of human resources to the features of the intangible base we observe that HIFs have a much larger stock of previously accumulated intangible assets (*ICI_PAST*) than both VIFs and LIFs. The same is true for the propensity to exploit asset complementarity (*D_COMPL*, i.e., dummy taking the value 1 if the firms simultaneously invested in "research and advertisement", "patens" and "licenses" for at least one year during the period 2001-2003 and zero otherwise): while the 23% of HIFs tends to exploit complementarity, this fraction reduces to 6% and 0% for VIFs and LIFs respectively. With reference instead to quality management standards, we observe that the fraction of firms having ISO 9000 standard (*D_ISO*) is larger for HIFs and VIFs compared to LIFs.

By looking at the variables related to the context in which firms operate, it is possible to identify some clear distinctions as well. HIFs tend to be more internationalised than both VIFs and LIFs in the sense of being oriented towards export (*D_EXPORT*) and facing international competitors (*D_COMPETITORS*). HIFs exhibit also a larger fraction of investment carried out in ICT equipment (*ICT_INV*) than both VIFs and LIFs. No particular difference emerge instead with respect to firm's age (*AGE*)

Overall, the descriptive statistics associated with HIFs, VIFs and LIFs tend to be aligned with the hypotheses formulated in Section 3. To have a clear test of the latter, we now proceed with a systematic empirical investigation.

5. Empirical strategy

We model the propensity to adopt a particular type of accumulation strategy as a function of two main types of variables. On the one hand, we consider systemic variables, such as the industry in which the firm operates. These variables are treated as controls in our analysis. On the other, we consider firm-specific characteristics, with particular attention being paid to human capital, intangible assets base, assets complementarity, and quality management standards. On this basis, we want to estimate the effect of each of such variables on the probability that a firm belongs to a different behavioural type, i.e., HIF, LIF, and VIF, during the period 2001-2008.

Formally, the model to be estimated takes the following form. Let $TYPE_i$ be a discrete variable defining the cluster firm *i* belonging to, i.e., *i*'s behavioural type. $TYPE_i$ can take three different values: 1 if a firm is HIF, 2 if a firm is VIF and 3 if a firm is LIF. Then, the probability that anyone of the behavioural type is observed is

$$\Pr(TYPE = k) = \frac{\exp(XF_i{}'\beta_F^k + XC_i{}'\beta_C^k)}{1 + \sum_{j=1}^{3} \exp(XF_i{}'\beta_F^j + XC_i{}'\beta_C^j)} \quad \text{for} \quad k = 1, 2, 3 \qquad (1)$$

where XF_i is a vector of firm-specific characteristics, XC_i is the vector of control variables, β_F^j and β_C^j are vectors of parameters, which are usually different for each *j* = 1, 2, 3. Equation (1) represents a standard multinomial logit model, which is estimated via maximum likelihood estimation.

All independent variables in equation (1) are evaluated at the beginning of the time span under analysis, i.e., taking into consideration the three-year period 2001-2003 – except for certain variables, for which we considered the period 2001-2004 (see below). In this way, we can control for all sorts of endogenous effects that may be derived from the simultaneous definition of both a firm's intangible accumulation profile and some of our independent variables. To control for omitted variable bias, not having the ability to add firm fixed effects (data are cross-sectional), we saturate the vector of controls with several variables that could be correlated with the decision to adopt a specific type of accumulation strategy, such as age size (*SIZE*), age (*AGE*), investments in ICT (*ICT_INV*), labour productivity, measured in terms of added value per employee (*LAB_PRDTY*), volatility of total assets (σ (*TOT_ASSETS*)), and whether the firm faces international competitors (*D_COMPETITORS*). In addition, we include a series of firm-specific accounting indexes such as financial autonomy (*FIN_AUTON*) (net worth over total assets, where the net worth includes equity, non-distributed shares and annual profit/loss), the profitability or gross earnings over total turnover (*PROFIT*) and the EBITDA (earnings before interest, taxes, depreciation and amortization) over total sales (*EBITDA*). Finally, we also control for geography-related effects with the introduction of regional dummies and for industries with the addition of dummies for Eurostat NACE Rev. 1 categories.

To represent the firm-specific characteristics that are the main object of our analysis, we consider the following variables. With respect to human capital, we consider a synthetic index elaborated with a factorial analysis (*FCT_EDU*) using as inputs the ratio between "white collar" and "blue collar" workers (*STAFFRATIO*), the workforce's average number of years of education (*AVEDU*) and the percentage of employees holding a university degree (*UNIDEG*). As a proxy for the degree of accumulated intangible capital, we consider a dummy taking the value 1 if the firm belongs to the fourth quartile of the lagged value of *ICI* (average 2001-2003) and 0 otherwise (*D_ICI_PAST*). The propensity to exploit assets complementarity is captured by a dummy taking the value 1 if the firms simultaneously invested in "research and advertisement", "patens" and "licenses" for at least one year during the period 2001-2003 and zero otherwise (*D_COMPL*). Finally, the adoption of quality management standard is measured with a dummy taking value 1 if the firms is certified UNI ISO 9000 in 2003 and 0 otherwise (*D_ISO*).

6. Results

Table 3 reports the multinomial logit estimates of our model, translated into marginal and impact effects for the continuous and dummy variables, respectively. The coefficients are obtained by computing estimates of the marginal effects for each firm in the sample and taking means of those effects.[9] Give the importance that is usually attributed to firm size in the literature on intangible assets, we report estimates of two distinct models: in the first

[9] Greene (1990) details methods for calculating the marginal effects and the associated standard errors.

one (Model A), we proxy the firm's size with the logarithm of *SIZE*; in the second one (Model B), we replace this continuous measure of size with two dummy variables for medium-sized (50 < *SIZE* ≤ 100) and large firms (*SIZE* > 100). The two models can be used as robustness checks with respect to the hypotheses defined in Section 3.

[Table 3 about here]

The first interesting result that we obtain concerns the firm's human capital (*FCT_EDU*). Whereas a one-unit increase in *FCT_EDU* positively and significantly impacts the probability of being HIFs, it does not significantly impact the probability of being either VIFs or LIFs. The size and significance level of the coefficients are highly consistent between Models A and B. This result lends support to the idea that adopting a persistent pattern of intangible assets accumulation necessarily requires some forms of highly qualified personnel. This is not the case instead for firms adopting discontinuous patterns of accumulation as well as firms that do not accumulate intangible assets at all.

Moving from the firm's human capital to the intangible asset base we find that the type of accumulation process tends to be strongly influenced also by the size of the intangible stock accumulated in the past (*D_ICI_PAST*). Having a large intangible asset base increases the probability of being HIFs, whereas it reduces the probability of being either VIFs or LIFs. In terms of coefficients, *D_ICI_PAST* has by far the strongest impact on the probability of being HIFs (both Models A and B), thus suggesting that for this type of firm, the existence of path dependency in the accumulation process plays a crucial role. Meanwhile, the negative sign associated with the probability of being VIFs suggests that firms adopting a discontinuous pattern of accumulation are characterized by a somewhat smaller size of the intangible assets base, which is probably not sufficient to profit from scale effects associated with a large intangible stock.

In addition to human capital and intangible assets base, the pattern of intangible assets accumulation tends to be strongly influenced also by the firm's propensity to exploit assets complementarity (*D_COMPL*). In both Models A and B this variable takes a positive and significant effect for HIFs and a negative and significant effect for LIFs. No significant effect is instead observed for VIFs. This result suggests that for HIFs the existence of technological complementarities in the asset stocks can be an important factor in pushing towards a persistent pattern of accumulation. On the contrary, no such effect seems to exist for VIFs who maintain a relatively greater degree of flexibility in planning investments.

An interesting result is found also for the variable associated with quality management standard (*D_ISO*). Differently from the previous variables, in this case we find that the recognition of ISO 9000 standard increases the probability of being VIFs while it reduces the probability of being LIFs. No effect is instead observed on the probability of being HIFs. Coefficients and significant levels are highly consistent between Models A and B. Considering the effects on HIFs, VIFs and LIFs together, this result lends support to the idea that although quality management standards generally increase the firm's propensity to accumulate intangible assets, this effect is more relevant for firms adopting a discontinuous pattern of accumulation than for those who accumulate persistently.

A careful inspection of the vector of control variables offers some interesting insights with respect to three additional factors. The first one is firm size (*SIZE*). As shown in Model A of Table 3, in fact, a larger firm has a greater probability of being either a HIF or VIF and a lower probability of being a LIF. A similar result is observed also in Model B, although in this case effect on VIFs tends to be weaker. This finding suggests that a firm's size matters for its propensity to accumulate intangible assets regardless of whether the accumulation process is persistent or discontinuous.

The second dimension along which control variables offer interesting results concerns the index associated with financial autonomy (*FIN_AUTON*). This variable takes a negative and (weakly) significant value in predicting the probability of being VIFs and a positive and significant coefficient in predicting the probability of being LIFs (both Models A and B). No significant effect is found for the probability of being HIFs. The combination of these results suggests that the financial condition of the firm is not a constraint in the adoption of a particular pattern of accumulation. This is true especially for LIFs, which appear as the most financially autonomous firms. On this basis we may conjecture that the adoption of a persistently low pattern of accumulation derives more from a deliberate choice rather than from a specific condition of the firms.

Finally, among the controls, we find a positive and significant effect associated with the dummy for export (*D_EXPORT*) in the case of HIFs and no significant effect for VIFs and LIFs. In our interpretation, this dummy captures the fact that firms compete in international markets mainly on the basis of product variety and innovativeness and they thus rely on intangible assets are a critical source of competitive advantage. In this sense, this result lends further support to the evidence concerning the positive relationship between intangible investments and export practices (López Rodríguez and García Rodríguez, 2005; Braunerhjelm, 1996). What this result adds to previous works is to suggest that firms with a high propensity towards exports are not only inclined to accumulate intangible assets but also tend to do so persistently.

Overall, the results of our estimates provide a fairly encouraging picture concerning the test of our theoretical hypotheses. First of all, partially in accordance with Hypothesis 1, we find human capital (i.e., *FCT_EDU*) to be a significant predictor of the probability of accumulating intangible assets, but only when this is done persistently. For firms that exhibit a discontinuous pattern of accumulation human capital does not seem to be a relevant trait. This suggests that, differently from HIFs, the discontinuous accumulation of intangible assets does not seem to be constrained by the relative lack of human capital.

With reference to Hypothesis 2, which concerns the role of the previously accumulated intangible stock, our main finding is that firms with a larger historical intangible assets base have a greater (lower) probability of persistently (discontinuously / never) accumulate intangible assets. This finding implies that firms with high intangible capital intensity at a given point in time tend to remain on the same technological trajectory, characterised by persistent accumulation. On the contrary, firms with a small intangible asset base are not technologically constrained and can adopt either a strategy characterised by persistently low intangible assets or a strategy based on a discontinuous process of accumulation. As argued in Section 3, the causal mechanisms underlying this trend may be related to (a) scale economies and (b) organisational learning. Although both factors may theoretically play a role, we are unable to distinguish between them based on our data.

Clear supporting evidence is also found with respect to Hypothesis 3, which concerns the propensity to exploit assets complementarity. Firms that at the beginning of the period simultaneously invest in different types of assets are more likely to persistently accumulated intangible assets than to discontinuously or never invest in intangible assets. The reason for this finding is essentially related to the combination of asset complementarities both across stock levels and across time, which in turn locks HIFs into persistent patterns of accumulation. The same is not true for VIFs and LIFs who rely on a more modular composition of the asset stocks and can thus enjoy greater flexibility in the accumulation process.

Finally, for Hypothesis 4, we find some evidence concerning the role of quality management standards. In both estimated models, we find that the coefficient associated with the presence of ISO 9000 standard is positive and significant in explaining VIFs, positive but not significant in explaining HIFs and negative and significant in explaining LIFs. This finding provides support for the hypothesis that quality management standards can indeed be an important instrument that favour the accumulation of intangible assets via a reduction of information asymmetries between buyers and sellers. This effect, however, seems to be limited to firms that are characterized by a discontinuous pattern of accumulation. One possible interpretation of this result is that quality management standards can help to sustain the external perception of a firm's quality only up to a certain threshold of the intangible stock. Beyond that threshold, other factors start to play an important role, such as for instance firm reputation.

7. Robustness checks

To increase the reliability of our results, we conduct a series of robustness checks.[10] First, we test alternative taxonomies for the industries, considering in particular the Pavitt's (1984) and the OECD (2009) classifications instead of Eurostat NACE Rev. 1 classification. The results show no significant changes with respect to our original estimates. For all our variables of interest, all coefficients maintain the same sign and degree of significance. In addition, the size of the marginal effects is of the same order of magnitude. On this basis, we can conclude that our hypotheses tend to be confirmed irrespectively of the taxonomy that we use for the industry.

Second, because several contributions have found a relatively strong effect of intangible assets on productivity (e.g., Marrocu et al., 2012), we also try different measures of productivity in our vector of control variables. In particular, apart from the value added per employee, we estimate total factor productivity using the method developed by Levinsohn and Petrin (2003). In this case too the results do not change.

[10] Tables are available from the authors upon request.

8. Conclusion

Considering the impact of intangible assets on performance, a positive and relatively constant process of accumulation is expected at the firm level. However, in reality, this is not the case: some firms accumulate very little intangible assets; many others exhibit discontinuous patterns of accumulation, and few accumulate persistently over time.

We provide an interpretive framework of these behaviours seeking to consider the adoption of different patterns of intangible assets accumulation in manufacturing firms. In particular, we identify three types of behaviour: high and persistent, discontinuous, and low and persistent. Using as a reference a broad theoretical framework that combines the capability-based view of the firm together with theories of technological complementarities and market signalling we define and provide support for a set of hypotheses on the determinants of such behaviours.

We focus on firm-specific characteristics, with particular attention being paid to human capital, historical intangible assets base, assets complementarity, and quality management standards. The verification of the hypothesis is based on a dataset containing economic and financial information concerning 1,130 Italian manufacturing firms and covering a period spanning from 2001 to 2008.

Multinomial logit estimates of our model show the following: first, the persistent accumulation of intangible assets is favoured by the internal availability of highly skilled personnel; second, firms with a) large intangible base and b) high propensity to exploit complementarities in the asset stocks are more likely to persistently accumulate intangible assets than to discontinuously or never accumulate intangible assets; third, the adoption of quality management standards facilitates the accumulation of intangible assets, especially if this is done discontinuously.

In sum, the paper provides an articulated representation of heterogeneous intangible assets dynamics in manufacturing firms and enriches our knowledge on the main variables impacting on intangible assets accumulation over time.

Based on these results, new interesting research questions open. First, it would be interesting to study how the behavioural types identified in this paper differentiate in terms of the nature of the intangible assets firms accumulate, for instance comparing externally purchased and internally developed assets. In order to address this question a somewhat thin decomposition of the intangible stock data is required. Secondly, an analysis aimed at deepening the study of complementarities in asset stocks would be of value; especially if it can offer some insights on how such complementarities can be exploited to improve firm performance.

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Appendix.

A1. Volatility of Intangible Capital Intensity

Taking into consideration a *n*-period time series for ICI_i^t, we define the weighted volatility of ICI_i^t as the standard deviation of *n*-years windows of ICI_i^t normalized by the *n*-years average level of ICI_i^t. Formally, we compute the weighted volatility of ICI_i^t as follows:

$$\sigma(ICI_i) = \frac{\sqrt{\sum_{t_0}^{t_0+n} (ICI_i^t - \overline{ICI}_i)^2}}{\overline{ICI}_i}$$

where $\overline{ICI}_i$ is the average of ICI_i^t between t_0 = 2001 and t_0+*n* = 2008. For the firms who reported ICI_i^t = 0 for all *t*, we directly imputed $\sigma(ICI_i) = 0$.

A2. List of the Variables

- *ICI:* % Intangible assets / tot. assets, average for the period 2001-2008.
- *σ (ICI)*: Volatility of *ICI.*
- *SIZE* (empl.): Number of employees, average for period 2001-2003.
- *D_SIZE_M*: =1 if SIZE 50 < *SIZE* ≤ 100.
- *D_SIZE_L*: =1 if SIZE > 100.
- *UNIDEG*: Graduated employees / tot. employees in 2003.
- *STAFFRATIO*: “White collars” / “blue collars”, average for the period 2001-2003.
- *AVEDU*: Workforce average education, average for the period 2001-2003.
- *ICI_PAST*: % Intangible assets / tot. assets, average for the period 2001-2003.
- *D_COMPL*: =1 if the firm simultaneously invested in all three assets (“research and advertisement”, “patents”, “licenses”) for at least one year during the period 2001-2003.
- *D_ISO*: = 1 if the firm is certified UNI ISO in 2003.
- *D_EXPORT*: = 1 if the firm has exported in 2003.

- *ICT_INV*: € Invested in ICT / tot. turnover, average for the period 2001-2003.
- *AGE*: 2010 less the year of foundation.
- *D_COMPETITORS*: = 1 if the firm faces International competitors.
- *LAB_PRDTY*: Added value per employee, average for the period 2001-2003.
- σ (*TOT_ASSETS*): Volatility of total assets.
- *FIN_AUTON* (Index): Net worth / tot. attest, average for the period 2001-2003, where net worth = equity + non-distributed shares + annual profit (or loss).
- *PROFIT*: Gross earnings / tot. turnover, average for the period 2001-2003.
- *EBITDA* (Index): Earnings before interest, taxes, depreciation and amortization over total sales, average for the period 2001-2003.

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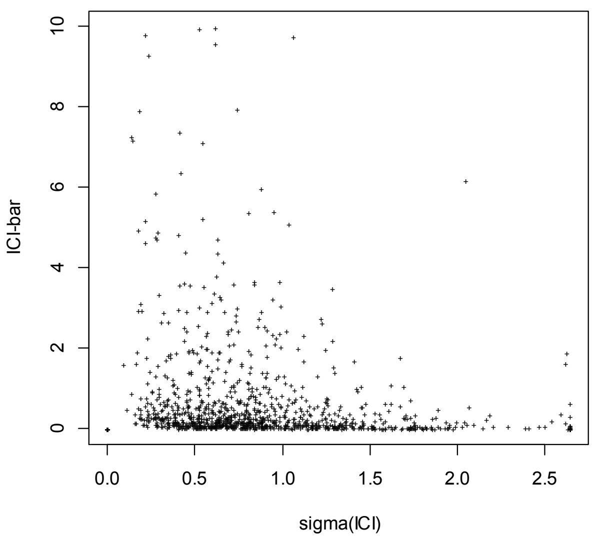
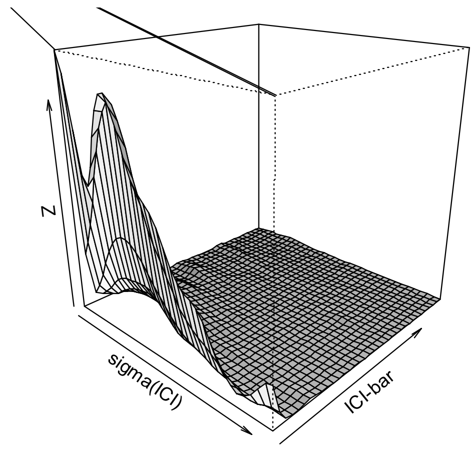
Figure 1 – Intangible assets investments and volatility

Panel A

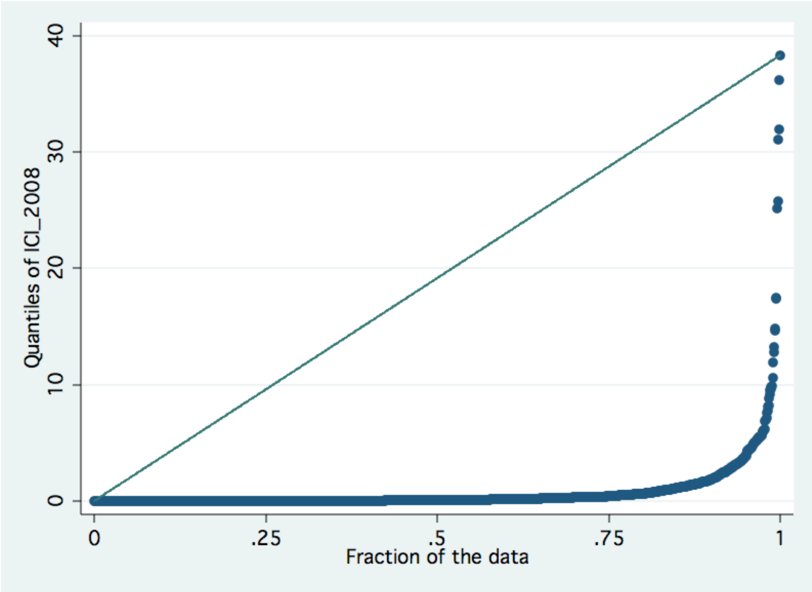


Panel B



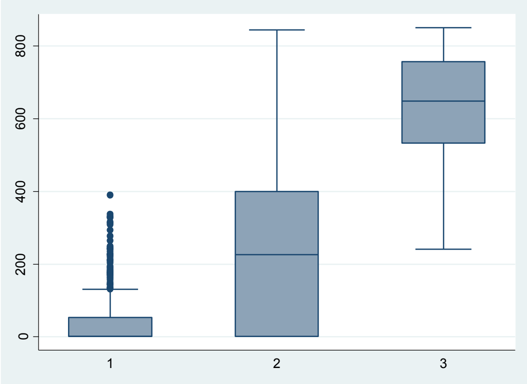
Legend: Panel A reports the two-way plot of the average level and volatility of ICI_i, for the time-span 2001-2008. Panel B reports the bivariate density estimation associated with Panel A. As it is easy see there exist three main groups of firms: those who invest very little in intangible assets, and do so persistently (peak on the left side of Panel B); those whose investments are on average low but highly volatile (central peak in Panel B); and finally, those who invest a large amount of resources in intangible assets, and do so persistently (long tail towards the north-east corner of Panel B).

Figure 2 – Quantile distribution of *ICI* for the year 2008.

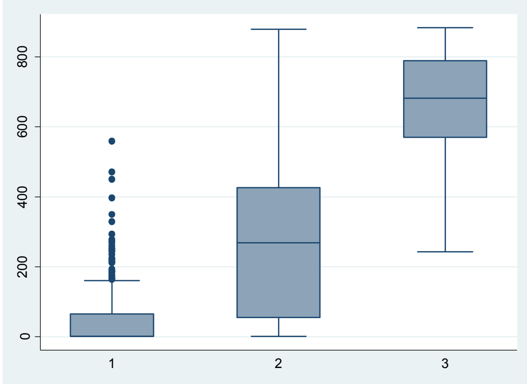


Legend: quantile distribution of the ratio intangible assets over total assets in 2008 for the sample of firms included in our dataset. The distribution shows that investments in intangible vary considerably across firms.

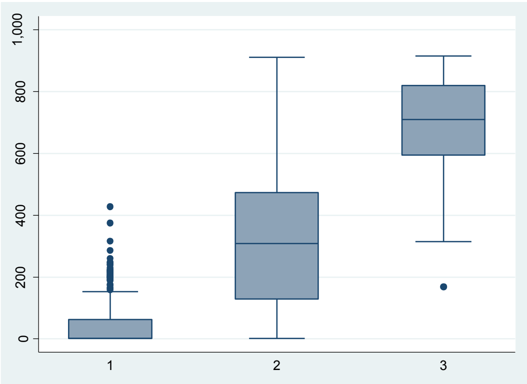
Figure 3 – Distribution of *ICI*-rank by firm clusters and year.



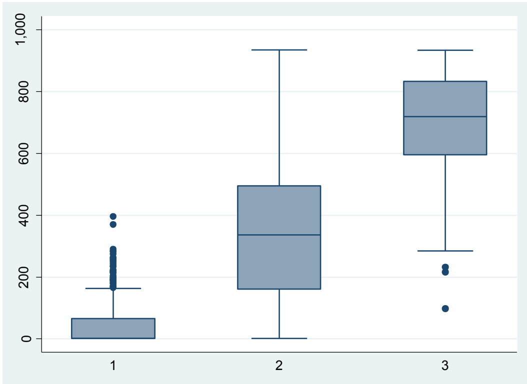
Year 2001; 1=LIFs, 2=VIFs, 3=HIFs.



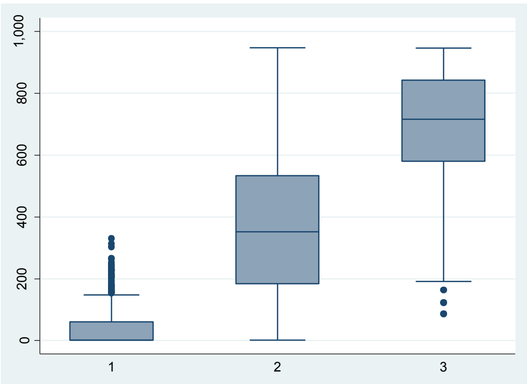
Year 2002; 1=LIFs, 2=VIFs, 3=HIFs.



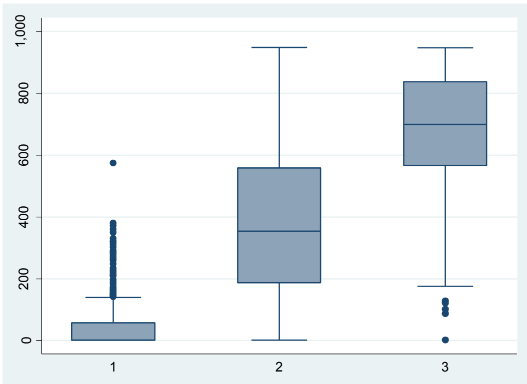
Year 2003; 1=LIFs, 2=VIFs, 3=HIFs.



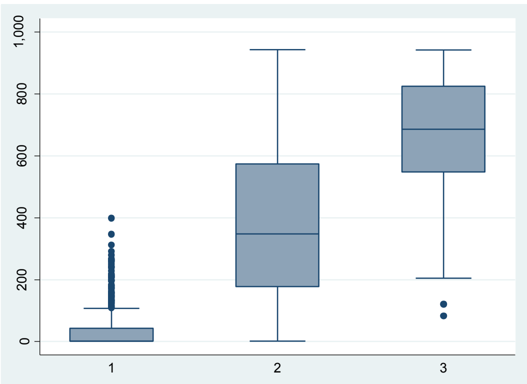
Year 2004; 1=LIFs, 2=VIFs, 3=HIFs.



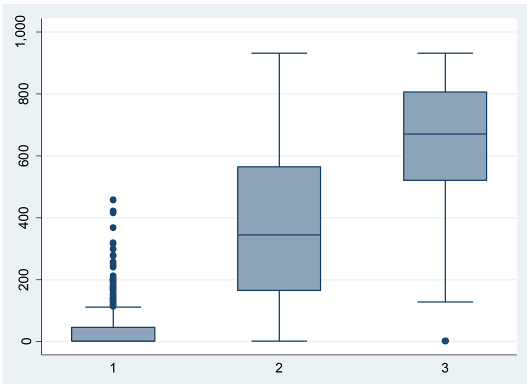
Year 2005; 1=LIFs, 2=VIFs, 3=HIFs.



Year 2006; 1=LIFs, 2=VIFs, 3=HIFs.



Year 2007; 1=LIFs, 2=VIFs, 3=HIFs.



Year 2008; 1=LIFs, 2=VIFs, 3=HIFs.

Tables

Table 1 – Rank-based Clusters Validation, k = number of clusters.

	ASW (1)	**P-GAMMA** (2)	**CH** (3)	**DUNN1** (4)	**DUNN2** (5)
k = 3	0.2988	0.5028	548.9742	0.0877	1.0918
k = 4	0.3012	0.5736	456.8676	0.0877	0.9741
k = 5	0.2509	0.5479	389.5179	0.0669	0.7704
k = 6	0.1991	0.4568	328.9468	0.0552	0.4850

Note: abbreviations ASW=average silhoutte width; P-GAMMA= Pearson Gamma; DUNN1= dunn minimum separation / maximum diameter. DUNN2= minimum average dissimilarity between two cluster / maximum average within cluster dissimilarity. For additional details see Halkidi et al. (2002).

Table 2 – Clusters' descriptive statistics

	All (1) (n. 1130)		HIFs (2) (n. 307)		VIFs (3) (n. 508)		LIFs (4) (n. 315)		
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**F-test**
ICI (%)	0.73	1.94	1.98	2.92	0.42	1.38	0.01	0.01	***
σ (ICI) (volatility)	0.77	0.58	0.54	0.26	0.97	0.49	0.68	0.80	***
SIZE (empl.)	90.70	123.74	120.65	167.78	87.65	104.60	66.42	92.06	***
UNIDEG	0.06	0.07	0.08	0.09	0.05	0.06	0.04	0.07	***
STAFFRATIO	0.72	2.40	1.05	3.54	0.56	0.99	0.65	2.61	**
AVEDU	10.34	1.39	10.68	1.43	10.30	1.34	10.07	1.38	***
ICI_PAST (%)	0.64	1.82	1.91	2.96	0.26	0.84	0.01	0.02	***
D_COMPL	0.09	0.29	0.23	0.42	0.06	0.23	0.00	0.06	***
D_ISO	0.59	0.49	0.64	0.48	0.62	0.49	0.50	0.50	***
D_EXPORT	0.79	0.41	0.89	0.31	0.77	0.42	0.71	0.46	***
ICT_INV (%)	2.93	9.55	3.69	4.61	2.94	11.76	2.20	9.11	
AGE	36.47	19.47	36.28	17.14	36.54	21.15	36.54	18.82	
D_COMPETITORS	0.09	0.29	0.11	0.31	0.09	0.28	0.09	0.28	

Legend: *=sig. 10%; **=sig. 5%; ***=sig. 1%

Table 3 – Results of the multinomial logit estimates, marginal effects for each category

	Model A			Model B		
	HIFs	**VIFs**	**LIFs**	**HIFs**	**VIFs**	**LIFs**
	b/se	**b/se**	**b/se**	**b/se**	**b/se**	**b/se**
FCT_EDU (index)	0.033**	0.000	-0.033	0.033**	-0.001	-0.033
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
D_ICI_PAST (d)	0.634***	-0.296***	-0.338***	0.634***	-0.295***	-0.339***
	(0.03)	(0.04)	(0.01)	(0.03)	(0.04)	(0.01)
D_COMPL (d)	0.163***	0.090	-0.254***	0.161***	0.093	-0.254***
	(0.05)	(0.06)	(0.03)	(0.05)	(0.06)	(0.03)
D_ISO (d)	0.018	0.062**	-0.079***	0.016	0.067**	-0.082***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
D_EXPORT (d)	0.053**	-0.011	-0.042	0.055**	-0.004	-0.050*
	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)
SIZE (ln_empl.)	0.034***	0.041**	-0.075***			
	(0.01)	(0.02)	(0.02)			
D_SIZE_M (d)				0.054**	0.004	-0.058**
				(0.02)	(0.03)	(0.03)
D_SIZE_L (d)				0.078***	0.063*	-0.141***
				(0.03)	(0.04)	(0.03)
LAB_PRDTY (index)	0.0010	0.0000	-0.0010	0.0010	0.0000	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FIN_AUTON (index)	-0.097	-0.166*	0.262***	-0.097	-0.158*	0.254***
	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)	(0.07)
D_COMPETITORS (d)	-0.008	-0.028	0.036	-0.002	-0.029	0.031
	(0.03)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)
Industry Dummies (NACE)	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Regional Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Other Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Obs	1130	1130	1130	1130	1130	1130
LogL	-836.03	-836.03	-836.03	-836.37	-836.37	-836.37
Chi2	745.104***	745.104***	745.104***	744.424***	744.424***	744.424***