ECONOMIC CRISIS AND FIRM EXIT: DO INTANGIBLES MATTER?

Intangible Asset Dynamics and Firm Behaviour

Alessandro Arrighetti[a], Fabio Landini[b,c] and Andrea Lasagni[a]

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[a]University of Parma, Department of Economics, via Kennedy 6, 43100 Parma.

[b]University for Foreigners of Reggio Calabria, MEDAlics, via del Torrione 95, 89125 Reggio Calabria, Italy

[c]Bocconi University, CRIOS, via G. Roentgen 1, 20136 Milan, Italy

Corresponding author:
Fabio Landini, Bocconi University, CRIOS, via G. Roenteng 1, 20136 Milan, Italy.
Tel: +39 02 5836 5171; e-mail: fabio.landini@unibocconi.it

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Abstract

We study the adoption of different patterns of intangible asset 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 asset 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 asset 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 asset 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 (IAs) in supporting the firm's performance has been widely claimed, in both academic and policy debates. 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 innovation, such as designs, software, blueprints, technology licences, and trademarks (Montresor and Vezzani, 2014). These resources are generally referred to as intangible assets and their contribution has been analysed with respect to different dimensions of economic activity (for a review see Conlon et al., 2012). At the macro-level growth-accounting exercises have shown that IAs explain a larger share of labour-productivity growth than tangible assets in a number of countries (Corrado et al., 2009; Marrano et al., 2009; Dal Borgo et al., 2013). At the micro-level several studies suggest the existence of a positive link between IAs and firm productivity (Marrocu et al., 2012; O'Mahony and Vecchi, 2009; Bontempi and Mairesse, 2008; Ceci and Masciarelli, 2010; Jiménez-Rodríguez, 2012; Hall et al., 2013; López-García et al., 2013), market value (Hall et al., 2005; Greenhalgh and Rogers, 2006; Sandner and Block, 2011; Hulten and Hao, 2008), and exports (Delgado-Gómez and Ramírez-Alesón, 2004). IAs have also become a focus of policy initiatives within the European Union.[1]

Although the literature on IAs is extensive, to date, there has been little empirical work at the firm level of the determinants of IA accumulation. One exception is Arrighetti et al. (2014), who uses balance sheet and survey data to study firms' propensity to invest in intangibles. This work finds a quasi-Pareto distribution in firms' propensity to invest, i.e., displaying high heterogeneity. In addition, the results show firm-specific features such as size, human capital and the historical intangible base which play a major role in explaining the propensity to invest.

Along these lines, one aspect that has still received relatively little attention concerns the dynamics underlying IA accumulation. In particular, no study has so far investigated the existence of different patterns of accumulation within firms. In theory, IAs are described as resources whose process of accumulation is highly persistent (see Teece, 1986; Dierickx

[1] See the Framework Research Projects like INNODRIVE, COINVEST, INDICER, and IAREG.

and Cool, 1989; Knott et al., 2003), so that the main differentiation is between those who invest and those who do not invest in these assets. Relatively little attention has instead been paid to the specific features of the investment pattern. This contrasts with recent trends in the economics of innovation literature, 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) as well as innovation persistence (Antonelli et al., 2013).

The relevance of studying the diversity of IAs dynamics emerges also from the data. In fact, careful examination of firms' behaviour (see Section 2) reveals that the pattern of accumulation may be more differentiated than typically thought. In our dataset, in particular, there are firms (approximately 55%) that exhibit highly persistent behaviour characterised by either very high or very low intangible investments. However, there are others (45%) that exhibit substantial discontinuities. The latter, in particular, alternate periods of positive investments with periods of relative stasis for an overall pattern 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 patterns among firms. Given that IAs 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 accumulation patterns? 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 streams of literature. The first one is the literature on the firm's learning and capabilities (Penrose, 1959; Teece, 1980; Nelson and Winter, 1982; Barney, 1991; Teece et al., 1997; Dosi et al., 2000), which focuses on the firm-specific resources that are necessary for IAs 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 accumulation process. The third one is the literature on market signalling (Spence, 1973), which stresses the need to complement strategies of IA 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. In particular, we focus on four variables: (i) human capital; (ii) historical intangible 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 algorithm. The theoretical hypotheses are tested on a rich dataset of Italian manufacturing firms.

Overall, we obtain three main results: First, we find that human capital is a key resource in favouring the accumulation of IAs, especially if this is done persistently. On the contrary, small human capital endowments are associated with either no or volatile modes of accumulation. Second, we find that firms with a larger intangible base and greater propensity to exploit complementarities have a greater probability of persistently accumulating IAs than to discontinuously or never accumulate IAs. Third, we find that the adoption of quality management standards facilitates the choice of accumulating IAs, especially if this is done discontinuously. With these results we contribute to the literature in two ways: First, we highlight the existence of great heterogeneity in the dynamics of IA accumulation; second, we provide an explanation for such heterogeneity 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 IA accumulation dynamics. Section 3 presents a brief overview of the literature and introduces our research hypotheses. Section 4 describes the procedure of classifying firms. Section 5 discusses the empirical strategy. Section 6 presents and discusses the results. Finally, Section 7 concludes.

2. Intangible asset dynamics: persistence or volatility?

IAs 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). Another motive is illustrated by Hall (2002) who observes that firms tend to smooth intangible investments (*e.g.*, R&D) to avoid firing knowledge workers and thus loose their embedded tacit skills. For these reasons, the main strategic problem faced by managers has often been associated with the process through which firms converge towards persistent paths of accumulation, being confident that such convergence can sustain competitive advantages over time.

This view, however, has been rarely confronted with real data. As suggested by Cuervo-Cazurra and Un (2009), nothing prevents the taxonomy of firm behaviours to be more variegated than the dichotomy between persistent investors and non-investors. Rather, the frequency of investments can be fairly differentiated and so is the set of strategic choices available to managers. Taking into account such differentiation is important for two reasons: first, because it poses a challenge to theory, which has often overlooked this issue; second, because it helps to go beyond the traditional distinction between intangible investors and non-investors, suggesting the existence of a broader set of behavioural types, in which choices of *ad-hoc* purchase of IAs can be correlated with specific necessity of output upgrading or to reactions to idiosyncratic demand. The latter point, in particular, can have significant implications for managers and policy makers in that it enlarges the set of strategies associated with the accumulation of intangibles.[2]

To verify the existence of persistent vs. discontinuous patterns of intangible accumulation we rely on two data sources. First, the IX wave of Capitalia's Survey, which covers the period 2001-2003 and contains qualitative and quantitative information, although with some limitations (see Cerrato and Piva, 2012), for a stratified sample of Italian manufacturing firms. Second, the AIDA-BVD database, which contains 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.[3]

The measure of IAs that we consider is the sum of three types of asset that are 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 subject to managers' discretion. The sum of these three assets is then normalised by 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 IAs accumulated by firm *i* in year *t*.

[2] For a similar point concerning the diversity of innovation activities see Malerba et al. (1997).
[3] Tables on sample representativeness are available from the authors on request.

Given this measure, we study the patterns of accumulation by considering two variables: the average level of ICI_i^t between 2001 and 2008 ($\overline{ICI}_i$) and its weighted volatility ($\sigma(ICI)_i$). The latter, in particular, is computed as the standard deviation of ICI_i^t between 2001 and 2008 normalised by $\overline{ICI}_i$ –see Appendix.[4] Figure 1 shows the relationship between these two variables: Panel A reports the observed values for $\overline{ICI}_i$ and $\sigma(ICI)_i$ on the vertical and horizontal axes, respectively; Panel B reports the associated kernel density function.[5]

[Figure 1 about here]

As we can see, firms' behaviour is far more differentiated than usually thought. First, we have the firms belonging to the peak on the left side of Panel B, corresponding to $\overline{ICI}_i = 0$ and $\sigma(ICI)_i = 0$ (plus some neighbouring points). These are firms that persistently accumulate very little IAs (very close to 0).[6] Second, towards the right, 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 IAs are 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 accumulate large amount of IAs and they do so persistently.

Overall, especially in light of the large number of firms that exhibit high volatility, Figure 1 reveals that, alongside differences in the levels of investment, the accumulation of IAs may also diverge in terms of dynamics. Firms undertaking highly persistent accumulation strategies co-exist with firms exhibiting huge discontinuities. The main aim

[4] Notice that the values reported in the firm's balance sheet refer to the stock of IAs, and not the flow. Still, since the measure is net of amortization (which is usually five years), we can capture discontinuities by looking at how the value of the intangible stock changes over time. Obviously, this stock measure reduces the average degree of observed volatility with respect, for instance, to a flow measure. However, this effect should be generalized and does not affect the relative stability of the accumulation process across firms.

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

[6] Although the combination $\overline{ICI}_i = 0$ and $\sigma(ICI)_i = 0$ appears as a single dot in Panel A, we know that it covers 157 observations, i.e., nearly 13% of the sample.

of the following sections is to investigate the origin of this heterogeneity.

3. Literature review and hypotheses

The existence of discontinuities in the accumulation of IAs is only apparently unexpected. Previous works have shown that some intangible-related investments such as R&D can be markedly discontinuous (Blazenko et al., 2012; Greve, 2003; Mudambi and Swift, 2011).[7] Moreover, these works have also shown that a large share of firms do not invest in R&D at all (Cohen et al., 1987; Galende and Suarez, 1999; Cuervo-Cazurra and Un, 2010), and that such differences persist even within narrowly defined industries (Ballester et al., 2003).

In addition to R&D investments, several authors have also focused on the diversity of firms' innovative dynamics. Virany et al. (1992) and Romanelli and Thusmann (1994), for instance, compare continuous and episodic organizational transformations, and investigate their impact on firm's performance. Roper and Hewitt-Dundas (2008) study the sources of innovation persistence and show the relevance of both the firm's internal resources and feedback received from the environment. Rush et al. (2007), finally, analyse the differences across firms' strategies of technological upgrading, distinguishing among: 'unconscious' firms, which are unaware of the need for technological change; 'reactive' firms, which respond to episodic challenges coming from the competitive environment; and 'strategic' firms, which adopt a strategic approach to continuous innovation. The latter contribution also emphasizes the relevance of detecting firms' behavioural archetypes for the design of policy initiatives.

Unlike this literature, most of the contributions on IAs (of which R&D is only a fraction) have neglected the issue of heterogeneity in the patterns of accumulation. Our contribution expressly aims at bridging that gap.

Our interpretative framework builds on the capability-based view of the firm and expands it with arguments from the theories of technological complementarities and market signalling. The capability-based view helps in identifying the resources that firms need

[7] This result partially contrasts with the smoothness of R&D investments reported by Hall (2002). A possible explanation for these contrasting views is offered by Cuervo-Cazurra and Un (2009) who suggest that what differentiates discontinuous R&D investors from persistent ones is that the former rely on both internal and external knowledge sources as opposed to only internal ones.

before IAs 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 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 accumulation of IAs depends on the adoption of complementary management tools that help firms to signal their market value.

On this basis, we focus on four variables: human capital, historical intangible base, technological complementarities, and quality management standards. The role of these variables will be analysed separately.

3.1 Human capital

Among the internal resources that can facilitate the strategic accumulation of IAs, one that has received particular attention is human capital. Several authors suggest that the quality of employees is a basic condition both for generating IAs and their economic exploitation (Galor and Moav, 2004). In this framework, human capital consists of formal education received by the workforce before hiring (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. 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 base.

At the same time, however, the accumulation and maintenance of human capital is costly for firms. Highly qualified personnel are paid higher wages and their contribution to firms' activities is difficult to monitor. This creates an incentive for firms with skilled personnel to persistently invest in other types of IAs, so as to profit form the available resources and avoid the risk of losing valuable tacit skills (Hall, 2002). In this respect Haskel and Pesole (2011) provide evidence in favour of a positive association between wage bills and different forms of intangible investments.

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

Hypothesis 1 – *A firm with a high level of human capital is more likely to persistently accumulate IAs than to discontinuously or never accumulate IAs.*

3.2 Intangible base

In addition to human capital, another internal resource that is likely to affect the accumulation of IAs is the historical intangible base, i.e., the stock of previous IAs. In this respect, several features of the IA accumulation process may be important, especially in differentiating persistent and discontinuous firms.

First, IAs consist of knowledge, which is cumulative by nature. Knott et al. (2003), for instance, suggest the existence of asset mass efficiencies in the generation of IAs from the existing asset stock. According to Dierickx and Cool (1989), asset mass efficiencies imply the existence of decreasing marginal costs in asset accumulation. 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 who made larger (smaller) investments in the past to make larger (smaller) and relatively more (less) persistent investments in the future.

Moving from the structural characteristics of IAs to features of the firm's behaviour, a similar argument can be formulated based on the idea of organisational learning (Dosi et al., 2006). In a nutshell, organisational learning suggests that when a firm adjusts its internal organisation to search the knowledge landscape and 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 period 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 that:

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

3.3 Complementarities

Another factor that can differentiate the patterns of IA accumulation is asset complementarities. As argued by Amit and Schomemaker (1993) asset complementarities refer to situations 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 (e.g. computer hardware and software). Investing in one specialized asset without simultaneously investing in the other makes the firms worse-off than investing in neither of the assets.

With particular reference to IAs, Knott et al. (2003) recognize asset complementarities as a key feature of their process of accumulation. A similar view is expressed also by Levinthal (1997), Levinthal and Warglien (1999) and Rivkin (2000), who focus on complementarities among organizational processes. Dierickx and Cool (1989) argue that asset complementarity is one of the factors that contribute to reduce the imitability of a firm's intangible stock.

The existence of asset complementarities has a direct impact on the process of IA accumulation. Since complementarities exist both across stock levels and across time, firms that exploit asset complementarities will tend to undertake an accumulation path that requires frequent and repeated investments. On the contrary, firms with a lower propensity to exploit complementarities may decide to discontinuously invest. As a consequence, depending on the technological features of the intangible base, different patterns of accumulation may emerge.

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

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

3.4 Quality standards

Finally, a factor that can affect the process of IA accumulation is the adoption of quality management standards. In this respect, Terlaak and King (2006) draw on Spence's (1973) theory of market signalling to argue that quality management standards (e.g. ISO) are primary instruments that firms use for signalling quality to their customers. In their view the usefulness of such tools is greater in contexts where the firm's internal characteristics are more difficult to evaluate. In these cases, in fact, the information asymmetries between buyers and sellers are particularly severe and quality standards can help to solve the problem. In support of this hypothesis Terlaak and King's (2006) find that the contribution of quality management standards to firms' performance is greater in industries where firms' attributes are more intangible.[8]

Based on this argument, we suggest that the presence of quality management standards can impact on the process of IA accumulation. Firms with quality management standards will be more inclined to accumulate IAs, because they are less worried about the impact that the latter may have on the external perception of their attributes. On the contrary, firms without quality management standards will be less inclined to do so, because of the unequal evaluation that market provides for such assets. Obviously, it is possible that such a relationship holds only up to a certain threshold of the intangible stock, after which other factors play a role in signalling the firm's quality (e.g., reputation). Whether this is effectively the case or not is mainly an empirical question.

On this basis, our fourth and last hypothesis is that:

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

[8] On the difficulty of market valuation of intangibles see also Bloch (2009).

4. Data and firm taxonomy

Before going into the detail of our empirical investigation let us point out some limitations of our data. As discussed in Section 2 our measure of IAs (ICI_i^t) is derived from the firm's balance sheets and refers to assets such as "research and advertisement expenditures", "patents" and "licenses". The latter are obviously a subset of the broader set of intangibles usually available within firms (see for instance Corrado et al., 2005). Moreover, balance sheet information is often subject to managers' discretion and this may create a bias in the way some expenditure is reported. To control for these possible issues we adopt two strategies. First, we focus our attention on the pattern of IA accumulation rather than on obtaining an estimate of asset value. Although a downward bias in our measure can certainly exist (because for instance not all types of intangibles are considered), it should affect all firms and years in the sample and it should not therefore distort the overall accumulation dynamics. Second, with respect to the bias in managerial reporting, we pay particular attention to exclude from our measure all assets whose capitalisation is highly subject to managers' discretion (e.g. goodwill). As a result all items that we consider should be objective expenses incurred by firms.[9]

Based on this data, the first step in our empirical investigation is to classify firms according to their accumulation profile. In doing so, the main difficulty that we encounter is related to the non-well behaved distribution of ICI_i^t. In each year, in fact, this variable takes value equal 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 is 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 based on this type of distribution would inevitably emphasize the difference in levels and undermine the heterogeneity of accumulation dynamics.

[9] One limitation of using balance-sheet data is that firms may fail to give full account of their IAs. This is true especially for firms that adopt international accounting standards such as the IAS38, which requires that research expenses be entirely expensed. Although this can be a problem in general, it is not relevant in our sample. According to Italian legislation (Law 306/2003 and Legislative Decree 38/2005), in fact, IAS38 applies only to firms that are listed in the Italian Stock Exchange, and our firms are not. Moreover, from preliminary interviews with some firms, we know that they are used to reporting research expenses as IAs in their balance sheet. This strengthens the confidence in our measure as good proxy of IAs.

[Figure 2 about here]

To obviate this problem we transform ICI_i^t so as to smooth its distribution. The large number of zeros limits the possibility of taking logs or compute growth rates. Alternatively, we transform ICI_i^t by considering ranks. First, for each year *t* between 2001 and 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 IAs of each firm relative to all the other firms included in the sample. Finally, we run Ward's linkage algorithm (Ward, 1963) on the set of r^t to identify clusters of firm profiles.[10]

The adoption of a rank-based classification presents both costs and benefits. On the cost side, it makes the accumulation profile of each firm relatively difficult to interpret because it becomes a function of the decisions taken by the other firms. On the benefit side, (a) it smooths the distance between firms with high *ICI* on the one hand and firms with medium and low *ICI* on the other, and (b) it increases the variability of accumulation dynamics, thus enabling the identification of different types of firm profiles. Overall, especially in light of the available data, we believe that this type of classification is a useful way to investigate the evolution of firm behaviours.

Given this classification procedure, we then proceed to validate the clusters. 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, however, that we 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. Version 2 of Dunn's index suggests that *k*=3 is the optimal number of clusters. All in all, given that three indexes out of five indicate *k*=3 to be the

[10] 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.

most meaningful solution, we adopt the latter as the main reference.[11]

[Table 1 about here]

The intuition of the presence of three main typologies of firms (i.e., those that persistently accumulate few IAs; those whose process of accumulation is low on average but highly volatile; and those that persistently accumulate a large amount of IAs) is confirmed by the cluster analysis. Table 2 reports the cluster means and standard deviations of *ICI*-rank for all years while imposing k=3. The last column of the table shows the result of an F-test on the difference between the cluster means. As we can see the three clusters distinguish in both the mean and variability of ranks. In particular, two groups of firms, those labelled 1 and 3 in the table, exhibit relatively high and low average rank, respectively, together with limited standard deviation. Meanwhile, one group of firms, labelled 2, is characterised by an intermediate average rank combined with large standard deviation. This suggests that the latter group exhibits wider variability in the values of *ICI*-ranks compared to the other two groups. The result of the F-test indicates that such variability, which could potentially influence the composition of the three groups, does not actually undermine the clusters' robustness. Altogether, these results suggest that although ranks are by themselves loose measures of firms' decisions, the clusters that we identified do capture part of the behavioural differences existing in the underlying data.

[Table 2 about here]

Some additional information on the cluster composition is reported in Table 3. The statistics refer both to the whole sample (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. In line with Table 2, clusters distinguish in both average level and volatility of *ICI*. At one extreme (column 2) there is a cluster of firms (27% of the sample) that on average exhibit a high level of <u>*ICI*</u> (1.98%) and relatively low volatility (0.54). We call this group High Intangible Firms (HIFs). At the other extreme (column 4), there is another

[11] According to the indexes the solution with k=4 is not very different from the one with k=3. The main difference is that with k=4 the algorithm splits the cluster of firms with a volatile profile into two, thus adding little insights. This finding reinforces our choice to keep k=3 rather than k=4.

cluster of similar size (28% of the sample) that on average exhibits a low level of *<u>ICI</u>* (0.01%) and low volatility (0.68). We call this group Low Intangible Firms (LIFs). In the middle there is a large cluster of firms (45% of the sample) that on average exhibit relatively low *<u>ICI</u>* (0.42%) but high volatility (0.97). We call this group Volatile Intangible Firms (VIFs). Each of these clusters represents a specific typology of firm behaviour.

[Table 3 about here]

The other statistics in Table 3 offer a more complete picture of the cluster characteristics (for a detailed description of the variables see Section 5). By comparing HIFs and VIFs against LIFs, we observe that the former two are 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 suggests that, although both HIFs and VIFs have more skilled personnel than LIFs, HIFs makes more systematic investments in human capital compared to VIFs.

Moving from human resources to the features of the intangible base we observe that HIFs have a larger stock of previously accumulated IAs (*ICI_PAST*) than both VIFs and LIFs. The same is true for the propensity to exploit asset complementarity (*D_COMPL*): while the 23% of HIFs 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.

The variables related to the context in which firms operate offer some interesting insights too. HIFs are 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 in ICT (*ICT_INV*) than both VIFs and LIFs. No particular difference emerge with respect to the firm's age (*AGE*)

Overall, the descriptive statistics associated with HIFs, VIFs and LIFs are aligned with the hypotheses formulated in Section 3.

5. Empirical strategy

We model the propensity to adopt a particular type of accumulation strategy as a function of two groups of variables. On the one hand, we consider systemic variables, e.g., the industry of activity, which are treated as controls in our analysis. On the other, we consider firm-specific characteristics, paying particular attention to human capital, IA base, asset complementarity, and quality management standards. In particular, we want to estimate the effect of these variables on the probability that a firm belongs to a behavioural type, i.e., HIF, LIF, or VIF, during the period 2001-2008.

Formally, our model takes the following form. Let $TYPE_i$ be a discrete variable defining the cluster firm *i* belonging to, i.e., *i*'s behavioural type. $TYPE_i$ is =1 if *i* is HIF, =2 if *i* is VIF and =3 if *i* is LIF. Then, the probability that any one of the behavioural types 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 period, i.e., taking into consideration the three-year period 2001-2003 – except for some variables, for which we considered the period 2001-2004 (see below). In this way, we can control for the simultaneous definition of both a firm's intangible accumulation profile and some of our independent variables.

For firm-specific characteristics we consider the following variables. Human capital is measured through a synthetic index elaborated with a factor analysis (*FCT_EDU*) using as inputs the ratio between "white collar" and "blue collar" workers (*STAFFRATIO*), the workforce's average years of education (*AVEDU*) and the percentage of employees holding a university degree (*UNIDEG*).[12] As a proxy for the intangible capital accumulated in the

[12] The principal component analysis method is used with Varimax rotation. Thus, the three indicators that proxy the quality of human capital are grouped into a single factor that explains approximately 98% of the

past, 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 asset complementarity is captured by a dummy taking the value 1 if the firms simultaneously invest in "research and advertisement", "patents" 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 firm is certified ISO 9000 in 2003 and 0 otherwise (*D_ISO*).

To control for omitted variable bias, not having the ability to add firm fixed effects (data are cross-sectional), we proceed in two stages. Fist we estimate a baseline model where we control only for number of employees (*SIZE*), age (*AGE*), geography-related effects (with regional dummies) and industry (with dummies for Eurostat NACE categories). Then, we check the strength of the identified effects by saturating the model with extra-controls. In particular we focus on variables that could be correlated with the adoption of an IA accumulation strategy, such as 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 has international competitors (*D_COMPETITORS*). In addition, we also include a series of 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 over total sales (*EBITDA*).

6. Results

Table 4 reports the multinomial logit estimates of our baseline 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

variance in the data. The validity of the factor analysis is examined by means of two tests. First, we use the Bartlett's Test of Sphericity to test the null hypothesis that the correlation matrix is an identity matrix, implying that the variables are uncorrelated. In our case, the significance value for this test (Chi-square 675.09 with 3 degrees of freedom) leads us to reject the null hypothesis. Secondly, the KMO Measure of Sampling Adequacy meets the minimum criteria, since for our data the value is 0.61.

sample and taking means of those effects.[13] Given the importance that is usually attributed to firm size, we report estimates of two distinct specifications: in the first one (Model A), we proxy the firm's size with the logarithm of *SIZE*; in the second one (Model B), we use two dummy variables for medium-sized ($50 < SIZE \leq 100$) and large firms ($SIZE > 100$). The two models can be used as robustness checks for our hypotheses.

[Table 4 about here]

The first result concerns the firm's human capital (*FCT_EDU*). Whereas one-unit increase in *FCT_EDU* positively and significantly impacts the probability of being HIFs, it does not impact the probability of being either VIFs or LIFs. Size and significance level of coefficients are consistent across models. This result suggests that adopting a persistent pattern of IA accumulation requires some form of highly qualified personnel. This is not the case for firms adopting discontinuous patterns of accumulation as well as firms that do not accumulate IAs at all.

As with human capital the intangible base (*D_ICI_PAST*) significantly affects the type of accumulation process. Having a large intangible 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). Meanwhile, the negative sign associated with VIFs suggests that firms adopting a discontinuous pattern of accumulation are characterized by an intangible base of smaller size, which is probably insufficient to profit from scale effects. Moreover this result excludes the possibility that VIFs are firms in transition (from HIFs to LIFs and *vice versa*).

In addition to human capital and the intangible base, the pattern of IA accumulation is influenced also by the exploitation of complementarities (*D_COMPL*). In both models *D_COMPL* takes positive and significant value for HIFs and negative and significant value for LIFs. A positive effect is observed also for VIFs, although only weakly significant. This result suggests that for HIFs the existence of technological complementarities can be an important factor in pushing towards a persistent pattern of accumulation. As we will see below such an effect is not robust for VIFs.

An interesting result is also found for the variable associated with quality management

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

standard (*D_ISO*). The recognition of the ISO 9000 standard increases the probability of being VIFs while it reduces the probability of being LIFs. No effect is observed for HIFs. Size and significant level of coefficients are consistent across models. 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 IAs, this effect is most relevant for firms adopting a discontinuous pattern of accumulation.

In Table 5 we check the robustness of the identified coefficients through the saturated model. As we can see most results also hold for this specification. The only difference is the coefficient of *D_COMPL* for VIFs, which is now not significant. This confirms the interpretation of VIFs as firms that, compared to HIFs, maintain greater flexibility in planning their investments.

[Table 5 about here]

A careful inspection of the control variables included in the saturated model offers some interesting insights too. The result for *SIZE* in Model A suggests that larger firms have greater probability of being either HIF or VIF and lower probability of being LIF. A similar result is also obtained in Model B, although the effect on VIFs is weaker. This finding shows that size matters for the decision to invest in IAs regardless of the accumulation profile.

The second dimension along which control variables offer interesting results is financial autonomy (*FIN_AUTON*). This variable takes negative and (weakly) significant value for VIFs and positive and significant value for LIFs (both models). No significant effect is found for the probability of being HIFs. The combination of these results suggests that the firm's financial condition is not a constraint in the adoption of a particular accumulation strategy. This is true especially for LIFs, which seem the most financially autonomous firms. In this sense the adoption of a persistently low pattern of accumulation seems more a deliberate choice of firms than the consequence of some specific condition.

Finally, among the controls, we find a positive and significant effect of the export dummy (*D_EXPORT*) for HIFs, while no significant effect is found for VIFs and LIFs. In our interpretation, this dummy captures the fact that firms compete in international markets mainly through product variety and innovativeness and they thus rely on IAs as key sources of competitive advantage. This result is in line with López Rodríguez and García Rodríguez (2005) and Braunerhjelm (1996).

Overall, the results of our estimates provide an encouraging picture for our hypotheses. First, in accordance with Hypothesis 1, we find human capital to be a significant predictor of the probability of accumulating IAs, but only when this is done persistently. For firms that exhibit a discontinuous pattern of accumulation human capital is not a relevant trait, i.e., its lack does not constrain firm behaviour.

With reference to Hypothesis 2 our main finding is that firms with a larger intangible base have greater (lower) probability of persistently (discontinuously/never) accumulating IAs. This finding implies that firms with high *ICI* tend to remain on the same technological trajectory, characterised by persistent accumulation. On the contrary, firms with a small intangible base are not technologically constrained and can differentiate their accumulation strategy. As argued in Section 3, the causal mechanisms underlying this trend may be related to scale economies and/or organisational learning. Based on our data, however, we are unable to distinguish between them.

Clear supporting evidence is also found for Hypothesis 3. Firms that at the beginning of the period simultaneously invest in different types of assets are more likely to persistently accumulate IAs than to discontinuously or never invest in IAs. Asset complementarities tend indeed to lock firms into persistent patterns of accumulation. The same is not true for firm that rely on a more modular composition of the asset stocks, which allows greater flexibility in the accumulation process.

With respect to Hypothesis 4, we find some evidence concerning the role of quality management standards. In all models, 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 are instruments that favour the accumulation of IAs by reducing the information asymmetries between buyers and sellers. This effect, however, is relevant only for firms exhibiting a discontinuous pattern of accumulation. One possible interpretation 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 a role, e.g., reputation.

Finally, to increase the reliability of our results, we conducted a series of robustness checks.[14] First, we test alternative taxonomies for the industries, considering the Pavitt's (1984) and the OECD (2009) classifications. 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, marginal effects are of the same size. Therefore, we can conclude that our hypotheses are confirmed irrespective of the industry taxonomy.

Second, because several contributions find that IAs have an effect on productivity (e.g., Marrocu et al., 2012), we try different measures of productivity in our vector of controls. In particular, apart from the value added per employee, we estimate total factor productivity following Levinsohn and Petrin (2003). Also in this case, the results do not change.

7. Conclusion

Given the impact of IAs 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 IAs; many others exhibit discontinuous patterns of accumulation, and few accumulate persistently over time.

In this paper we provide an interpretive framework for this behavioural heterogeneity. In particular, we find that: a) the persistent accumulation of IAs is favoured by the internal availability of highly skilled personnel; b) firms with a large intangible base and high propensity to exploit assets complementarities are more likely to persistently accumulate IAs than to discontinuously or never accumulate IAs; and c) the adoption of quality management standards facilitates the accumulation of IAs, especially if this is done discontinuously.

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 IAs, for instance comparing externally purchased and internally developed assets. This issue is perceived as relevant in several recent studies. For example, Montresor and Vezzani (2014) show that internally developed intangibles have a greater impact on firm innovativeness than externally purchased ones. To address this question, however, a

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

detailed decomposition of data is required. Second, an analysis aimed at deepening the study of complementarities in asset stocks would be of value; especially if it can offer some insights into how such complementarities can be exploited to improve firm performance.

But perhaps in terms of further research the most relevant questions concern the possible evolution of VIFs. There is sufficient evidence to argue that appropriate policies to transform their conduct from unstable to stable investment could positively affect their performance. So rather than implementing undifferentiated policies to support the accumulation of intangibles in all firms and industries, it may be reasonable to try selective policies focused on firms that have initiated an accumulation process but risk remaining stuck midway in a condition of fragility.

Appendix.

Consider 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:

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

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 $\sigma(ICI_i) = 0$.

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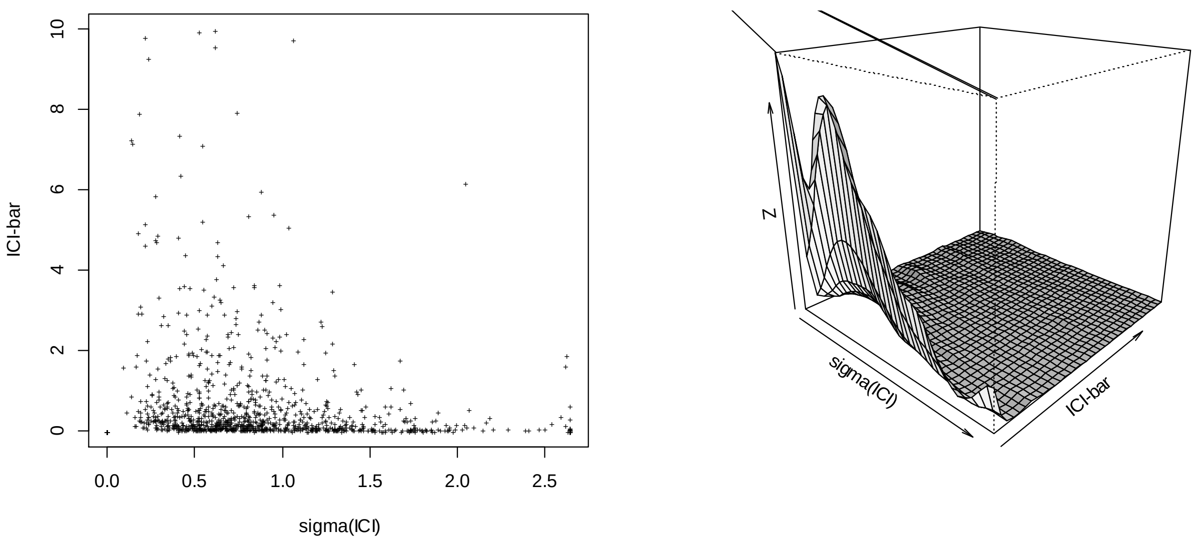
Figures

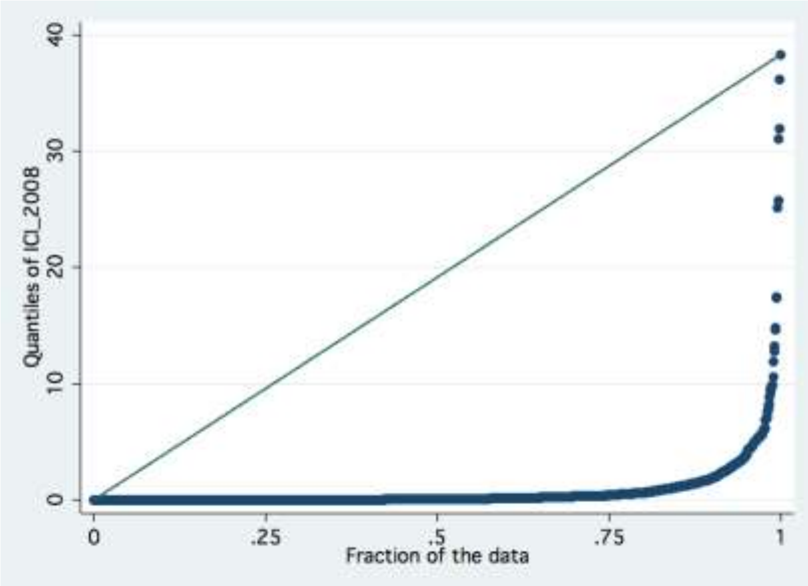
Figure 1 – Intangible assets investments and volatility

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.

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 – Difference in ICI-rank by firm clusters and year

	Cluster (1) (n. 307)		Cluster (2) (n. 508)		Cluster (3) (n. 315)		
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**F-test**
Rank 2001	632.42	142.79	248.63	223.25	42.52	80.30	***
Rank 2002	671.25	137.52	274.54	222.09	47.30	88.76	***
Rank 2003	698.13	143.72	313.48	228.63	42.31	74.94	***
Rank 2004	703.62	157.80	338.68	238.44	42.50	75.29	***
Rank 2005	696.21	174.89	367.83	245.52	40.54	72.75	***
Rank 2006	683.44	185.45	377.11	252.70	43.23	84.28	***
Rank 2007	673.67	175.91	376.81	257.90	37.56	72.91	***
Rank 2008	651.71	187.67	371.16	260.09	39.22	78.31	***

Note: Higher values of the rank means that positions within the ranking are closer to the top. Legend: *=sig. 10%; **=sig. 5%; ***=sig. 1%

Table 3 – 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 4 – 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**	-0.008	-0.025	0.035***	-0.008	-0.026
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
D_ICI_PAST (d)	0.641***	-0.298***	-0.343***	0.641***	-0.297***	-0.344***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
D_COMPL (d)	0.162***	0.096*	-0.258***	0.160***	0.099*	-0.259***
	(0.05)	(0.06)	(0.03)	(0.05)	(0.06)	(0.03)
D_ISO (d)	0.013	0.070**	-0.083***	0.012	0.074**	-0.086***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
SIZE (ln_empl.)	0.034***	0.032*	-0.066***			
	(0.01)	(0.02)	(0.02)			
D_SIZE_M (d)				0.051**	-0.003	-0.048*
				(0.02)	(0.03)	(0.03)
D_SIZE_L (d)				0.078***	0.05	-0.128***
				(0.03)	(0.04)	(0.03)
AGE	0.000	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Regional Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Obs	1130	1130	1130	1130	1130	1130
LogL	-852.803	-852.803	-852.803	-853.102	-853.102	-853.102
Chi2	711.559***	711.559***	711.559***	710.961***	710.961***	710.961***

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

Table 5 – Results of the saturated model, marginal effects for each category

	Model A (saturated)			Model B (saturated)		
	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)
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)
AGE	0.000	0.000	0.000	0.000	0.000	0.000
	(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_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)
Industry Dummies	*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***

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