

THE VALUE OF KNOWLEDGE: DISCOVERING HIDDEN CAPITAL

Massimo Cecchi *

* Department of Business and Economics (DISEI), University of Florence, Florence, Italy
Contact details: Department of Business and Economics (DISEI), University of Florence, Via delle Pandette, 9, 50127 Florence, Italy



Abstract

How to cite this paper: Cecchi, M. (2023). The value of knowledge: Discovering hidden capital. *Corporate Ownership & Control*, 20(3), 221–231.
<https://doi.org/10.22495/cocv20i3art14>

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ISSN Online: 1810-3057
ISSN Print: 1727-9232

Received: 08.03.2023
Accepted: 31.05.2023

JEL Classification: M4, M5, M12
DOI: 10.22495/cocv20i3art14

The purpose of this research is to overcome the weaknesses of intellectual capital (IC) estimation models, constructing and empirically verifying a new model that has the same strengths as the value-added intellectual coefficient (VAIC) but not its weaknesses. To better outline our analysis with respect to the many meanings that can be evoked by the term IC in the literature, we also define a new term: “hidden capital” (HDC) in the balance sheet. First, we analyze the epistemological and methodological aspects of the models existing in the literature, highlighting their weak points. Subsequently, using a logical-deductive methodology, we build a theoretical model, named “HDC”, to discover the “hidden capital”. Finally, we proceed to the empirical verification of the HDC model on a sample of over 1,800 listed European companies observed in the pre-pandemic period 2011–2019 (over 10,000 firm-year observations). The empirical verification through a regression panel model on eight European countries shows that all the variables of the HDC model are, unlike VAIC, significant and directly correlated to Tobin’s Q.

Keywords: Intellectual Capital, Hidden Capital, IC, VAIC, Tobin’s Q, European Listed Companies

Authors’ individual contribution: The Author is responsible for all the contributions to the paper according to CRediT (Contributor Roles Taxonomy) standards.

Declaration of conflicting interests: The Author declares that there is no conflict of interest.

1. INTRODUCTION

In the most advanced economies, knowledge increasingly represents the main strategic asset, as a resource precious, rare that is not easily accessible and replaceable.

However, determining the value of the knowledge available to a company has proven to be very complex. The related scientific research has moved in two main directions.

The first direction identifies knowledge as a type of “intellectual capital” (IC) normally not captured by financial accounts and capable of generating a surplus of return. This relationship is then reversed by identifying the presence of IC in companies with a surplus of return. However, this does not seem acceptable. In fact, while companies that use little knowledge can have high returns, companies that use knowledge inefficiently can have low returns.

The second direction, essentially identifying knowledge in the value of human capital (HMC), seeks to evaluate it as an asset on par with other investments. However, even this solution does not seem convincing. Companies do not control this investment in knowledge, as employees can leave, which dissolves the accumulated HMC, forcing new investments in training and offering rival organizations opportunities to acquire knowledge. It is precisely for these reasons that accounting principles do not allow for the inclusion of these investments among balance sheet assets.

Therefore, a new rationale is proposed in this paper, focusing on two main considerations.

The *first consideration* is that the identification of a knowledge-based process as a process characterized by “high value-added” has probably led to a misunderstanding. In fact, schematically, if we set $EBIT = VA - HC - DA$, (where, VA indicates the value added, HC indicates the cost of human

resources and *DA* indicates depreciation and amortization), a process with “high-value-added” should not be translated as “with high *VA*” but with a process that adds high value to input (goods and services) bought externally and thus, “with high *HC* and *DA*”, representing the flow value of the human and technological knowledge employed, respectively. The difference is substantial, as considering *VA* also includes in knowledge-based processes those that use resources of poor quality and value but that have a high-profit margin while considering *VA* excludes processes that use resources of high quality and value but that have a low profitability margin.

The *second consideration* is that human capital and technology are very fluid investments.

Human resources, as previously mentioned, are not controlled, but investments in advanced technology can also deteriorate very quickly. Therefore, the attempt to capitalize on these flows seems to be a research dead end.

Instead of distinguishing between “tangible” and “intangible” capital, we believe that it is more useful to distinguish between “visible” and “hidden” capital in the balance sheet. Even if our research is undoubtedly among that on *IC*, we prefer not to use this term due to its assumed multiple meanings in the literature.

Therefore, a company normally invests in “visible” capital, quantified by the total value of tangible and intangible assets, that is, all investments that can be capitalized according to Generally Accepted Accounting Principles (GAAP). This stock of conventional visible total assets (*TA*) also includes activities that normally do not add value to production in a strict sense, such as financial assets, inventory, and buildings.

However, we also have other investments with high value-added but that are extremely fluid, whose true value cannot be expressed in the balance sheet, and that for this reason, we refer to as “hidden capital” (*HDC*).

By following this approach, we identify the hidden capital in the flow value of human (*HC*) and technological (measured by *DA*) resources used in the production process.

We, therefore, create an *HDC* ratio that sums two new ratios, *HCV* (human capital value) and *TCV* (technical capital value), which, respectively, measure the use of human and technological resources compared to competitors.

The research hypothesis assumes that *since the nonrecognition of hidden capital assets reduces the significance of the balance sheet, while investors determine market value, considering all available information, at the same profitability and other conditions, the greater the hidden capital measured with HDC is, the greater the difference between a company's book value and market value.*

The empirical verification is carried out by selecting approximately 1,800 European listed companies, observed from 2011 to 2019, for a total of 10,950 firm-year observations.

The competitor comparison takes place, instead, by tracing medians on over 438,000 listed and unlisted European companies.

We find that the *HDC* model, like the value-added intellectual coefficient (*VAIC*) model, uses simple calculations, verifiable and comparable

indicators. However, we also find that the *HDC* indicators, unlike those of *VAIC*, are theoretically correct and significant in explaining some of the differences between a company's book value and market value.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature. Section 3 further explains the *HDC* model, formulates the hypotheses, and explains the methodologies used. Section 4 explains the data collected and sets forth the descriptive statistics. Section 5 empirically verifies the *HDC* model and discusses the results. Section 6 concludes the paper.

2. LITERATURE REVIEW

The valuation of immaterial assets such as knowledge has always been critical. In the early 1900s, Veblen (1904) noted that “the substantial foundation of the industrial corporation is its immaterial assets” (p. 143) and that “there may be particular difficulties in the way of reducing this goodwill to the form of a fund, expressing it in terms of a standard unit” (p. 171).

Undoubtedly, many changes have occurred since then. If, in modern economies, on the one hand, intangible assets have become increasingly important, then on the other hand, knowledge has been increasingly encoded in algorithms, standards, procedures, software, patents, etc.

However, while codified knowledge is transmissible and, therefore, evaluable by the market, uncoded knowledge often remains an investment that resides mainly in people, that is, a type of *HMC* that is transmitted through the transfer of people themselves.

Attempts to include *HMC* among balance sheet assets can be traced back to models such as the opportunity-cost model (Hekimian & Jones, 1967), replacement cost model (Flamholtz, 1973), and discounted wage and salary model (Lev & Schwartz, 1971). However, these methods, which require very subjective and, therefore, unreliable assessments, have always been considered unacceptable according to GAAP.

In fact, according to the framework of the International Financial Reporting Standards (IFRS), to be recognized on the balance sheet, an asset must be an economic resource that is reliably measurable and controlled by the entity, and it must be probable that the future economic benefits derived from the asset will flow to the entity (IAS 38.21). *HMC* is not even fully controlled, as employees can leave by depleting the accumulated *HMC*, not allowing for reliance on future benefits, forcing new investments in training, and offering opportunities for rival organizations to acquire such knowledge (Coff, 1997; Hatch & Dyer, 2004; Lepak & Shaw, 2008; Shaw et al., 2013).

HMC is, therefore, essentially a current cost to be charged to the income statement, which, according to IAS (IAS 1.99), must be indicated separately or specified in the notes. US GAAP, conversely, does not require any mandatory specification, although, in 2020, the Securities and Exchange Commission (SEC) amended the S-K regulation precisely to require listed companies to describe their *HC* assets.

This growing demand for HMC disclosure has also prompted companies to voluntarily include detailed reports in various corporate documents, such as annual reports, environmental reports, and corporate social responsibility reports. (Khan & Khan, 2010; Macagnan & Fontana, 2013; Abhayawansa & Guthrie, 2016; Druz et al., 2020). Moreover, in recent years, a new way in which to organize information relating to HMC has emerged through “integrated reporting” (IR), the framework of which, promoted by the International Integrated Reporting Council (IIRC), provides for the “dissemination of information relating to people” precisely (IIRC, 2021, p. 19).

However, the problem remains, as the growing push to broaden the boundaries of financial statements non strictly through accounting information (Lev & Zarowin, 1999) does not diminish the importance of defining objective, reliable, and comparable valuation methods for uncodified knowledge.

In recent decades, the evaluation of HMC and, more generally, of noncodified knowledge has increasingly been inserted into the broader context of the estimation of IC.

However, the main models highlight various criticalities, often fragile under the epistemological aspect and/or open to manipulation under the reliability aspect.

Even if, given the number of criticalities, it is impossible to do a complete review, those that are best known should be taken into account.

The direct intellectual capital methods (DICM) and scorecard methods (SM) break down and analytically evaluate the various associated intangible elements (e.g., customer loyalty, number of patents, know-how, training of human resources, and structural assets such as information systems). Then, these models reaggregate and organize the above elements into a global and multidimensional measure that, in the case of the SM, takes the form of a scorecard. Among the DICM, some measures are the “technology broker” (Brooking, 1996), “citation-weighted patents” (Bontis, 1996), and Value Explorer™ (Andriessen & Tiessen, 2000). Among the MS, some measures are the “balanced scorecard” (Kaplan & Norton, 1992), “Sandia Navigator™” (Edvinsson & Malone, 1997), “intangible asset monitor” (Sveiby, 1997), “IC Index™” (Roos et al., 1997) and the “value creation index” (Low, 2000).

These methods, at the epistemological level, face the problem that in an attempt to differentiate and personalize themselves (many of them are trademarks of consulting firms), they transform the concept of “IC value” into a myriad of different meanings. At the operational level, the analysis of heterogeneous data perspectives on IC, which is very useful for internal and strategic purposes, does not provide a tool with which external stakeholders can understand and compare the value of an organization’s IC.

Market capitalization methods (MCM) are other financial methods that identify the value of IC with the capital market premium, i.e., the excess of a company’s market capitalization over its stockholders’ equity. Among these methods, some commonly used ones are the “Investor Assigned Market Value” (IAMV™) and market-to-book value methods (Stewart, 2003; Luthy, 1998).

At the epistemological level, these methods are consistent with the definition of HDC to argue that with the same profitability and visible capital, hidden capital that is not recognized in the balance sheet but appreciated by the market can lead to a difference between book value and market value. However, the problem with these methodologies is that cause (HDC investments) and effect (market appreciation) are interchanged and overlapped. Therefore, these methods only allow for a hypothetical measure of the overall effect of HDC but tell us nothing about the causes.

Return on assets (ROA) methods are heterogeneous financial methods based on the idea that hidden assets increase profitability expressed by the return on company assets at the same book value. This relationship is then reversed by identifying the presence of IC in all companies with a surplus of return.

At the epistemological level, these methods also overlap cause (the existence of hidden capital) with supposed effect (greater profitability) but implicitly also presuppose that hidden capital is used efficiently. Only in this way, in fact, can such investment lead to greater profitability. However, the inverse relationship that predicts higher profitability as an indicator of hidden capital does not seem acceptable. In fact, the ROA also increases in cases of the heavy exploitation of low-skilled and underpaid workers, which is exactly the opposite of the concept of valuable hidden capital.

Moreover, at the methodological level, these methods are very sensitive to the interest rate assumptions used for the capitalization of surplus income.

Although the Knowledge Capital Earnings Method (KCE™) method is still a financial method, it differs in its attempt to identify the surplus generated by IC as the difference between the overall economic result and the return generated by physical and financial capital (Lev & Mintz, 1999).

At the epistemological level, even KCE™, as a ROA method, does not question whether the greater profitability is derived from the exploitation of a low-skilled and underpaid workforce. Therefore, KCE™ cannot select situations of highly knowledgeable employees. At the methodological level, this method is also dominated by arbitrary computational factors, such as the expected relationship between the return on physical and financial capital and the discount rate for intellectual capital.

The best-known financial model, however, is probably the Value Added Intellectual Coefficient (VAIC™) model, which, as intended by its creator (Pulic, 1998, 2000, 2008), reformed the entire approach to the evaluation of IC.

The model starts from the value-added relationship, fully derivable from book value:

$$VA = OUT - IN = OP + HC + D + A \quad (1)$$

where, VA is the value added OUT is the total sales; IN is the external cost of purchasing materials, components, and services; OP is the operating profit; HC is the personnel costs; D is depreciation; and A is the amortization of assets.

VAIC™ is the result of the sum of three efficiency ratios, all obtained through

the combination of the value added (VA), personnel costs (HC), Pulic's definition of structural capital ($SC = VA - HC$), and the book-value of the capital employed in tangible assets (EC):

- Human capital efficiency ($HCE = VA/HC$);
- Structural capital efficiency ($SCE = SC/VA = (VA - HC)/VA$);
- Capital employed efficiency ($CEE = VA/CE$).

In particular, efficiency in the use of intangible resources or intellectual capital efficiency (ICE) is measured by:

$$ICE = HCE + SCE \quad (2)$$

This method, which has the simplicity of the application as one of its main strengths, nevertheless presents numerous criticalities both from an epistemological and an empirical point of view. For more details, the relevant literature can be consulted (Andriessen, 2004; Stähle et al., 2011; Iazzolino & Laise, 2013). According to Stähle et al. (2011), the "VAIC indicates the efficiency of the company's labor and capital investments and has nothing to do with IC. Furthermore, the calculation method uses overlapping variables and has other serious validity problems" (p. 531).

The widespread application of this method and the use of financial statement parameters, however, makes it the ideal candidate for comparison, even empirical, with the HDC model.

3. METHODOLOGICAL FRAMEWORK

Our research, therefore, aims to overcome the limitations of previous methodologies by using a different approach.

First, unlike many other methodologies, we clearly distinguish causes from effects, as investing in capital, visible or hidden, does not imply that such capital also has an adequate return.

The identification of a knowledge-based process as a "high value-added" process has probably led to a misunderstanding. Schematically, if we set $EBIT = VA - HC - DA$, a process with "high value-added" should not be translated "with a high VA " and thus higher ROA , $VAIC$, VA/TA , etc., as such a decision depends on "how" the hidden investment is used.

A process characterized by "high value-added" is a process that adds high value to inputs (goods and services) bought externally, "with high HC and DA " representing the flow value of the human and technological knowledge employed, respectively.

The difference is substantial, as the consideration of VA is also included in knowledge-based processes that use resources of poor quality and value but that have a high-profit margin while excluding processes that use resources of high quality and value but that have a low profitability margin.

Second, instead of distinguishing between "tangible" and "intangible" capital, we believe that it is more useful to distinguish between "visible" and "hidden" capital on the balance sheet. A company normally invests in "visible" capital, quantified by the total value of tangible and intangible assets, that is, all investments (total assets or TA) that can be capitalized according to GAAP. However, we also have other more fluid investments that according to

accounting principles, cannot be entered into the balance sheet and which, for this reason, we refer to as HDC. Given the extreme slipperiness of the term "IC" and the overlap of many measurement models and related variables partially previously examined, it is preferred that such terms not be used and that the object of study be reformulated and redefined as HDC.

This established, we first consider the value of human capital (HCV) as a type of hidden capital made up of the value of the people at the disposal of a company that competes on knowledge.

In a perfectly active and competitive theoretical market, the value of people is measured by the money they are willing to pay to guarantee their availability but also taking into account that the legal relationship that guarantees this availability is not ownership but rather an employment contract. Hence, a potentially much more unstable bond makes this investment much more fluid.

In fact, a company can have a highly qualified workforce only if it is willing to pay it adequately on an ongoing basis since, at any time, a worker can choose to switch to one of the company's competitors if they are going to be paid more. In addition, this is true both for the one acquired directly on the market and for that formed internally. For this reason, many approaches that identify the evaluation of human resources in investment in training are also not convincing. If a person who is trained is not then recognized by an adequate salary increase, then it is likely that he or she will relocate to a company that recognizes these greater skills with a salary increase. In this sense, remuneration already includes the measure of investment in training.

The next question concerns the actual perfect competitiveness of the labor market.

In fact, we can hypothesize that there are at least two forms of borders in the flow of the workforce.

The first border concerns the sector. That is, we can imagine that skills and knowledge are developed and optimized mainly within one sector and that a leading knowledge worker in one sector probably would not have the same position in another sector. Thus, each sector has its own skills that can be recognized by offering employees different salary levels.

The second border concerns the geographical border for at least two reasons. The wage level of highly skilled employees is usually linked to a country's cost of living. Moreover, work does not have the same mobility as other resources. In fact, the free movement of the workforce is not always guaranteed by the laws of various states. Furthermore, it is inevitable that the transfer of the workforce, unlike the transfer of capital or other productive factors, involves the transfer of the entire lives of individuals and families. Therefore, an ultra-national allocation of the best human knowledge on the basis of the best salaries alone is not a conceivably perfect approach.

In summary, we can assume that among the companies that bet on HCV, the competition to secure the best knowledge workers is within a national sector, that the investment in HCV is a sort of "liquid investment", and that precisely for

this reason, unlike other assets, it can flow into companies with a higher salary level, particularly within the same nation sector.

It follows that “personnel cost” is not only a negative component of the income statement but also an investment that must be used efficiently. Those who compete in terms of knowledge thus also compete in terms of high cost and value.

The next step, therefore, leads us to devise an indicator to evaluate the investment in human capital that takes into account the abovementioned factors.

Like with other methods (e.g., VAIC and cost methods), we also start from the personnel cost of an HC company. However, since the total cost does not tell us anything about the amount of remuneration paid by the company, we first determine the average cost per employee, a human capital value (*hcv*), that is:

$$hcv_i = \left(\frac{HC}{\text{number employees}} \right)_i \quad (3)$$

At this point, it is plausible to say that a company in a certain sector and in a particular nation pays its employees more than its competition and is thus able to attract the most qualified employees on average. In summary, it can be argued that on average, a company that has higher *hcv* attracts, average, more skilled employees than does a company with lower *hcv*.

Therefore, if we calculate a median *hcv* for a given sector (*s*) and country (*c*), then we may suppose that the companies that focus more on human capital are those that have a higher *HCv* value (*HC value*), where *HCv* is as follows:

$$HCv_i = \frac{hcv_i}{hcv_{s,c,median}} \quad (4)$$

From software houses to consulting companies and from universities to mechanical industries or restaurants, it is plausible that the companies that focus on the quality of their employees are those that in a perfectly flexible market, pay them more than the median.

Those companies who, conversely, fall well below the abovementioned level, far from the median, may perhaps also have a very high efficiency in the use of human resources (as in the case of *HCE* in Pulic’s model) and, with it, even higher profits, but in our opinion, such companies cannot be considered as focusing on the knowledge and quality of *HC*.

As we are always in search of hidden capital, we then consider another investment: the flow of investments in technology that participates in the production process, referred to as “technical capital value” (*TCV*). Therefore, we are not referring to the stock of total “visible” assets on the balance sheet “*TA*” (which also includes credits, inventories, etc.), but rather to the flow of resources used for production (i.e., depreciation and amortization “*DA*”).

To make this measure homogeneous with *hcv*, we also divide the flow of resources used by the number of employees, determining an index of

technical capital value (*tcv*) per employee, employed in production:

$$tcv_i = \left(\frac{DA}{\text{number employees}} \right)_i \quad (5)$$

Additionally, in this case, the intensity of this hidden capital employed is determined with *TCv* through a comparison with the overall median of the sector without distinguishing the country, as the technology market, unlike that of human resources, is undoubtedly much more globalized.

$$TCv_i = \frac{tcv_i}{tcv_{c,median}} \quad (6)$$

These two indicators give us a measure of the average quality per employee, compared to the competition, of the human (*HCv*) and technological (*TCv*) resources employed in the production process. However, to determine the quantity or the overall value of the flow used in the production process, it is also essential to consider the production structure, the intensity of human capital (numerosity) in relation to the total invested capital “*hcn*”, that is:

$$hcn_i = \left(\frac{\text{number employees}}{\text{Total Assets}} \right)_i \quad (7)$$

For technology, and unlike human resources, with *HCn*, we then compare the company to its competitors without distinguishing its country. It is, in fact, conceivable that even in configuring its production structure, the company competes in increasingly global markets because the markets to which it supplies products and services are becoming increasingly global and interconnected.

$$HCn_i = \frac{hcn_i}{hcn_{c,median}} \quad (8)$$

We can, therefore, measure the total value of the human capital of an *HCV* company by multiplying the average quality per employee, (*HCv*), by the intensity of human capital *HCn*:

$$HCV_i = HCv_i \times HCn_i \quad (9.1)$$

HCV becomes a linear transformation of *HC/TA* when there are no differences between sectors and countries with $k_1 = 1/(hcv_{median} \times hcn_{median})$, which is a constant among the cases analyzed:

$$HCV_i = \frac{HC_i}{TA_i} \times k_1 \quad (9.2)$$

In the same way, we measure the total value of the technological capital of a *TCV* company by multiplying the average quality per employee, (*TCv*), by the intensity of human capital *HCn*:

$$TCV_i = HCt_i \times HCn_i \quad (10.1)$$

TCV becomes a linear transformation of *DA/TA* when there are no differences between sectors and

countries with $k_2 = 1/(hct_{median} \times hcn_{median})$, which is a constant among the cases analyzed:

$$TCV_i = \frac{DA_i}{TA_i} \times k_2 \quad (10.2)$$

Finally, we calculate an overall hidden capital index (*HDC*) as follows:

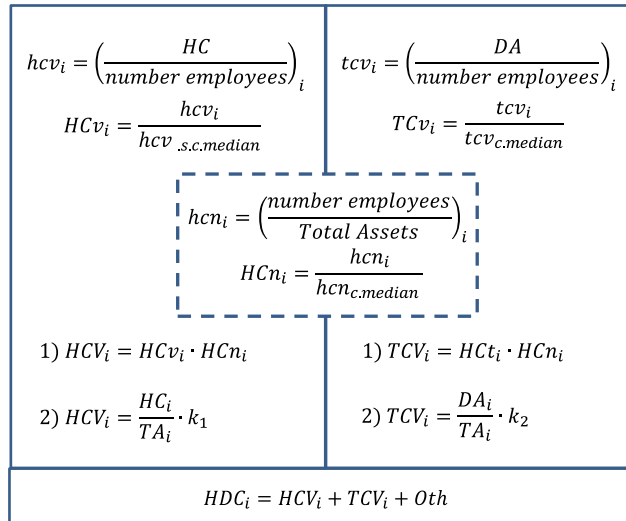
$$HDC_i = HCV_i + TCV_i + Oth \quad (11)$$

$$HDC_i = HCN_i(HCV_i + TCV_i) + Oth \quad (12)$$

where *Oth* denotes other hidden capital that can possibly be aggregated to the *HDC* formulation.

Figure 1 summarizes the steps and variables described.

Figure 1. Summary of model variables



As anticipated, the failure to recognize invisible assets inevitably reduces the significance of financial statements. However, investors determine market value, taking into account all available information, including that derived from the value of hidden assets (Fama, 1970). This has equally and inevitably led to the growing difference between the market value of the company as perceived by investors and its book value as indicated in its financial statements.

Therefore, if *HDC* is a measure of this hidden capital, then our research hypothesis is as follows:

H1: Under the same profitability and other conditions, the higher the HDC value is, the greater the difference between book value and market value.

To verify this hypothesis, we set up a series of regression models that use *Tobin's Q* (*TbQ*) as a dependent variable.

Initially, we consider only the control variables, that is:

- visible capital, i.e., the book value of controlled resources compared to those owned ($lev = TA/E$);
- profitability, expressed by *ROE*;
- total assets resulting from financial statements (*TA*), expressed as a natural log ($size = LnTA$);
- sector and country as dummy variables.

The first model, which includes only the control variables, is, therefore, as follows:

Model 1

$$TbQ = \alpha_0 + \alpha_n \text{Control Variables} + \varepsilon \quad (13)$$

We then examine the predictive capacity of the VAIC model, which, in addition to being one of the most popular, also uses financial statement ratios:

Model 2

$$TbQ = \alpha_0 + \alpha_1 HCE + \alpha_2 SCE + \alpha_3 CEE + \alpha_n \text{Control Variables} + \varepsilon \quad (14)$$

Ultimately, since the VAIC model is an efficiency index that relates the VA to the resources employed, the predictive capacity of the VA/TA ratio is as follows:

Model 3

$$TbQ = \alpha_0 + \alpha_1 \frac{VA}{TA} + \alpha_n \text{Control Variables} + \varepsilon \quad (15)$$

Subsequently, the predictive ability of the return on visible capital, or the ROA, is as follows:

Model 4

$$TbQ = \alpha_0 + \alpha_1 ROA + \alpha_n \text{Control Variables} + \varepsilon \quad (16)$$

To deepen the analysis of ROA, we break down the numerator (i.e., EBIT) into the difference between value added (VA) and the flow of internal resources used (HC and DA):

Model 5

$$TbQ = \alpha_0 + \alpha_1 \frac{VA}{TA} + \alpha_2 \frac{HC}{TA} + \alpha_3 \frac{DA}{TA} + \alpha_n \text{Control Variables} + \varepsilon \quad (17)$$

Therefore, let us check the *HDC* model, which, as seen, considers only the flow of resources used.

First, we use the simplest model (indicated as (2) in Figure 1):

Model 6

$$TbQ = \alpha_0 + \alpha_1 \frac{HC}{TA} + \alpha_2 \frac{DA}{TA} + \alpha_n \text{Control Variables} + \varepsilon \quad (18)$$

Finally, the model compares the resources used with the medians (indicated as (1) in Figure 1):

Model 7

$$TbQ = \alpha_0 + \alpha_1 HDV + \alpha_2 TCV + \alpha_n \text{Control Variables} + \varepsilon \quad (19)$$

4. RESEARCH METHOD AND DATA SAMPLE

To compose the sample, we extract data from the AMADEUS database by selecting a very large sample of European companies from Austria (AT), Belgium (BE), Germany (DE), Spain (ES), France (FR), Great Britain (GB), Ireland (IE) and Italy (IT).

We select only medium to large companies with a minimum turnover of €20 million, total assets of at least €10 million, and at least 100 employees, and

we observe them for 9 years during the pre-pandemic period, namely, from 2011 to 2019.

To determine their market value, we select companies that were listed as of May 2021 (1,807). Not all the selected companies were listed during the selected period; moreover, after removing the outliers, we obtain 10,950 firm-year observations.

The medians $hcv_{s.c.median}$, $hcn_{c.median}$ and $tcv_{c.median}$ are calculated for companies that met the requirements again in May 2021 (60,952). Not all companies, however, published their financial statements from 2011 to 2019. Hence, the total number of firm-year observations is 435,252. To take into account long-term wage variations over these 9 years, we construct the median hcv over two intervals, 2011–2015 and 201–2019, while we deem the 2011–2019 period sufficient for tcv .

Tables 1 and 2 present the observations by sector and country for the sample of listed companies used to verify the HDC model and the overall sample used to calculate the medians. As can be seen, the composition of the samples, from both qualitative and quantitative points of view, is clearly affected by the productive structure of each country and, for the listed sample (Table 1), by the size of the stock market.

Table 1. Distribution of data of listed companies by sector and country

NACE codes	Countries								Total
	AT	BE	DE	ES	FR	GB	IE	IT	
n.i.			10	9	9	307			335
01-10	12	26	74	65	66	274	18	138	673
11-20	8	48	388	100	320	676	10	279	1,829
21-30	8	7	63	28	84	181		97	468
31-40	27	42	124	106	211	899	20	127	1,556
41-50	16	15	48	35	167	323	27	82	713
51-60	45	58	329	264	688	740	18	166	2,308
61-70	101	23	608	91	824	548	78	221	2,494
71-80		4	31	8	69	258	32	9	411
81-99			36	5	10	97		15	163
Total	217	223	1,711	711	2,448	4,303	203	1,134	10,950

Note: NACE codes means Statistical Classification of Economic Activities in the European Community (from French term *Nomenclature statistique des activités économiques dans la Communauté européenne*).

Table 2. Distribution of data of the overall sample by sector and country

NACE codes	Countries								Total
	AT	BE	DE	ES	FR	GB	IE	IT	
n.i.	2	3	4			796	25		830
01-10	530	1,184	2,034	3,937	3,195	6,741	133	2,934	20,688
11-20	1,071	1,856	3,915	3,549	4,053	5,966	156	6,706	27,272
21-30	3,303	3,000	15,989	8,837	11,117	14,351	558	20,521	77,676
31-40	531	430	4,261	1,789	2,988	6,695	163	4,213	21,070
41-50	4,452	6,010	14,815	15,462	21,703	33,003	1,143	14,424	111,012
51-60	675	1,204	2,462	3,846	4,010	8,642	447	3,309	24,595
61-70	1,583	3,666	20,964	9,705	12,365	24,854	2,126	13,491	88,754
71-80	585	1,245	3,785	3,480	4,553	8,927	273	2,474	25,322
81-99	897	922	11,851	3,963	4,268	15,089	810	3,233	41,033
Total	13,629	19,520	80,080	54,568	68,252	125,064	5,834	71,305	438,252

Note: NACE codes means Statistical Classification of Economic Activities in the European Community (from French term *Nomenclature statistique des activités économiques dans la Communauté européenne*).

Table 3. Distribution of data of listed companies by year and country

Year	Countries								Total
	AT	BE	DE	ES	FR	GB	IE	IT	
2011	21	21	49	72	246	389	15	83	896
2012	20	26	43	67	260	405	17	105	943
2013	21	27	39	64	257	414	20	108	950
2014	18	23	227	69	263	443	26	110	1,179
2015	18	25	242	79	263	474	26	120	1,247
2016	28	26	262	80	275	508	28	131	1,338
2017	30	28	271	91	284	546	26	151	1,427
2018	33	27	285	94	299	559	27	160	1,484
2019	28	20	293	95	301	565	18	166	1,486
Total	217	223	1,711	711	2,448	4,303	203	1,134	10,950

Tables 3 and 4 present the composition of the two samples in relation to the years in question. Since the extraction refers to May 2021 for the financial statements from 2011 to 2019, we note that not all the selected companies have published financial statements in previous years (according to Table 3, from 41,071 in 2011 to 50,584 in 2019) or they were listed (according to Table 3, from 896 in 2011 to 1,486 in 2019). Furthermore, in May 2021,

not all the 2019 financial statements were entered into the database, so in some cases, their number decreased slightly in the final year of the study period (e.g., according to Table 4, from 55,877 in 2018 to 50,584 in 2019).

Table 5 presents the descriptive statistics. From the VA/TA indicator, we can see that cases with negative value added are excluded.

Table 4. Distribution of data of the overall sample by year and country

Year	Countries								Total
	AT	BE	DE	ES	FR	GB	IE	IT	
2011	1,370	1,992	6,711	5,416	6,859	11,270	460	6,993	41,071
2012	1,383	2,040	6,329	5,571	7,136	11,867	501	7,171	41,998
2013	1,415	2,081	6,089	5,776	7,302	12,538	556	7,143	42,900
2014	1,459	2,113	9,226	5,988	7,483	13,300	605	7,671	47,845
2015	1,518	2,180	9,611	6,253	7,694	14,082	690	7,969	49,997
2016	1,617	2,230	10,203	6,521	7,861	15,044	768	8,260	52,504
2017	1,663	2,296	11,122	6,778	8,179	15,999	853	8,586	55,476
2018	1,667	2,321	11,363	6,727	8,114	16,116	800	8,769	55,877
2019	1,537	2,267	9,426	5,538	7,624	14,848	601	8,743	50,584
Total	13629	19,520	80,080	54,568	68,252	125,064	58,34	71,305	438,252

Table 5. Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
TbQ	10950	0.549	0.19	0.005	0.997
ROA	10950	0.063	0.105	-1.94	2.517
VA/TA	10949	0.365	0.256	0.00	3.046
HC/TA	10949	0.255	0.23	0.00	2.899
DA/TA	10949	0.047	0.051	0.00	1.457
HCV	10932	0.947	0.802	0.00	11.678
TCV	10932	1.507	1.89	0.00	84.268
HCE	10950	2.102	2.97	0.007	104.601
SCE	10950	0.272	1.86	-135.682	0.99
CEE	10939	0.533	0.431	0.00	5.31
ROE	10950	7.593	45.451	-911.326	932.973
Size	10950	13.177	2.119	6.802	20.66
Lev	10950	3.269	7.772	1.004	342.651

Table 6. Pearson correlation

Variables	TbQ	ROA	VA/TA	HC/TA	DA/TA	HCV	TCV	HCE	SCE	CEE	ROE	Size	Lev
TbQ	1.000												
ROA	-0.147***	1.000											
VA/TA	-0.010	0.365***	1.000										
HC/TA	0.051***	0.026**	0.921***	1.000									
DA/TA	0.025**	-0.349***	0.110***	0.061***	1.000								
HCV	0.050***	0.028***	0.739***	0.790***	0.089***	1.000							
TCV	0.021**	-0.310***	0.132***	0.106***	0.827***	0.057***	1.000						
HCE	-0.021**	0.128***	-0.169***	-0.251***	0.022**	-0.241**	-0.016*	1.000					
SCE	0.015	0.153***	0.022**	-0.047***	0.007	-0.047***	0.001	0.096***	1.000				
CEE	-0.043***	0.229***	0.802***	0.755***	0.143***	0.575***	0.185***	-0.153***	0.018*	1.000			
ROE	-0.052***	0.581***	0.184***	-0.011	-0.229***	-0.008	-0.201***	0.067***	0.106***	0.116***	1.000		
Size	0.298***	0.056***	-0.299***	-0.347***	-0.054***	-0.306***	-0.079**	0.214***	0.076***	-0.238***	0.082***	1.000	
Lev	0.324**	-0.057***	-0.034**	-0.012	-0.001	0.008	0.001	-0.008	0.000	-0.043**	0.058**	0.103***	1.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. RESEARCH RESULTS AND DISCUSSION

Pearson correlation coefficients are computed to examine the strength and direction of the relationships between all the variables studied (see previous Table 6).

The table shows how all variables are significantly correlated with Tobin's Q (*TbQ*), with only two exceptions: *CEE* for the VAIC model and *VA/TA*.

Regression analysis. For all the models, variance inflation factor (VIF) indicates that there are no multicollinearity problems. However, there are other problems. The modified Wald statistic reveals

heteroskedasticity. Furthermore, Shapiro-Wilk and Shapiro-France tests indicate that the variables are not normally distributed. However, the limited number of years examined does not present problems of serial correlation.

Therefore, we use regression with cluster-robust standard errors and, to choose between fixed or random effects, a robust version of the Hausman test that indicates that fixed effects are preferable. The same results are given by the Sargan-Hansen statistic. Unfortunately, in using a fixed effects model, we must forgo dummy variables.

The regression results are shown in Table 7. Model 1 shows that all control variables (*ROE*, *Size*

and *Lev*) are significantly related to *TbQ* and that the goodness of fit (R-squared) is 9.7%.

Model 2 introduces the VAIC variables. *HCE*, *SCE*, and *CEE*, none of which are significant, and the goodness of fit (R-squared) remains at 9.7%.

Model 3 introduces *VA/TA* variables, which are weakly significant ($p < 0.1$), and their goodness of fit (R-squared) only grows to 9.9%.

Model 4 introduces *ROA* variables. Again, as in the previous models, we use a variable that measures efficiency.

However, since $ROA = \frac{EBIT}{TA} = \frac{VA}{TA} - \frac{HC}{TA} - \frac{DA}{TA}$ we also take into account the flow value of human (*HC*) and technological (*DA*) resources used in the production process. *ROA* is a significant variable, and the goodness of fit (R-squared) grows to 10.8%.

Model 5 analyzes the *ROA* in more detail, breaking it down into its components *VA/TA*, *HC/TA*, and *DA/TA*. All three components are significant, but the most important aspect is

the negative sign of the coefficient of the variable *VA/TA* which seems to confirm that hidden capital is not directly related to *VA* but rather to *HC* and *DA*. The goodness of fit (R-squared) grows to 11.8%.

Models 6 and 7 test the previously described *HDC* model.

Model 6 introduces the variables *HC/TA*, and *DA/TA*, and then tests the simpler model *HDC* (with $HCV = \frac{HC}{TA} \times k_1$ and $HDC = \frac{DA}{TA} \times k_2$) without medians. Both variables are significant, and although the model differs from the previous one in terms of the elimination of the *VA/TA* variable, the goodness of fit remains almost the same (11.4%).

Finally, Model 7 tests the complete *HDC* model, that is the one that calculates *HCV* and *TCV* using medians. As we can observe, both indices are significant, and the goodness of fit (R-squared) grows to 11.6%.

These findings confirm the research hypothesis of there being a positive relationship between *HDC* and *Tobin's Q*.

Table 7. Regression analysis

Variables	TbQ						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
<i>HCV</i>							0.031*** (4.20)
<i>TCV</i>							0.003** (2.31)
<i>HC/TA</i>					0.211*** (4.79)	0.120*** (3.71)	
<i>DA/TA</i>					0.193*** (4.75)	0.162*** (4.49)	
<i>VA/TA</i>			0.047* (1.93)		-0.097*** (-2.80)		
<i>ROA</i>				-0.143*** (-5.09)			
<i>HCE</i>		-0.001 (-1.23)					
<i>SCE</i>		-0.001 (-1.13)					
<i>CEE</i>		0.000 (-0.03)					
<i>ROE</i>	0.000*** (-7.76)	0.000*** (-7.53)	0.000*** (-8.02)	0.000*** (-7.53)	0.000*** (-5.53)	0.000*** (-6.67)	0.000*** (-6.73)
<i>Size</i>	0.025*** (4.43)	0.025*** (4.41)	0.029*** (5.12)	0.026*** (4.43)	0.035*** (5.91)	0.035*** (6.05)	0.036*** (6.00)
<i>Lev</i>	0.003*** (3.70)	0.003*** (3.70)	0.003*** (3.70)	0.003*** (3.61)	0.003*** (3.59)	0.003*** (3.64)	0.004*** (3.49)
Constant	0.214*** (2.91)	0.215*** (2.85)	0.148*** (1.95)	0.210*** (2.75)	0.051*** (0.62)	0.037*** (0.47)	0.036*** (0.44)
Obs.	10,950	10,937	10,949	10,950	10,949	10,949	10,932
R-squared	0.097	0.097	0.099	0.108	0.118	0.114	0.116
F-test	28.040	14.880	23.189	28.625	27.892	27.892	27.225
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6. CONCLUSION

In conclusion, the empirical analysis conducted in the previous paragraph seems to confirm what was hypothesized at the theoretical level.

Since hidden capital, appreciated by investors but not recognized in financial statements (all other conditions being equal), increases the gap between market value and book value, we find that the variables of the VAIC model (*HCE*, *SCE*, and *CEE*) are not significant in explaining this gap expressed through *Tobin's Q*.

ROA is significant, but by breaking it down, we observe something interesting: efficiency expressed

by *VA/TA*, even if significant, is paradoxically negative. The variables *HC/TA* and *DA/TA*, instead, are significant and directly related to *Tobin's Q*.

This finding seems to demonstrate the previously supposed misunderstanding. Identifying a knowledge-based process as a process characterized by "high value-added" should not be translated as "with a high *VA*" but with a process that adds high value to goods and services bought externally, thus "with high *HC* and *DA*".

Then, we test the *HDC* model that we have built, both in the simplest form with *HCV* and *TVC* as *HC/TA* and *DA/TA*, and in the more complex

form. All the variables are significant and directly related to *Tobin's Q*.

Our research hypothesis is, therefore, statistically confirmed.

Thus, the *HDC* model, which uses objectively determinable indicators that are simple but theoretically coherent, in our opinion, can have interesting implications, both theoretical and practical, in the evolution of research on high-knowledge technology companies.

Subsequent improvements certainly are possible. For example, at the research level, although model testing involves a large data collection process, the medians can be even more specific. From a practical point of view, the individual company can also calculate more specific medians to identify its approximate positioning in investments in human and technological capital compared to that of its competitors.

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