The Impact of Intangible Inputs on Investments and Market Power: Analysis of the Italian Case

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Abstract

Intangible assets lack physical substance: they include the value of a brand name, firm-specific human capital, patents and trademarks, software and databases. I document the rise of these assets in the Italian Economy during the last 20 years. Also, I find proof of a growing investment gap, defined as the difference between actual physical investment and what would be predicted by valuation measures. I show that this gap is attenuated when I take into account intangible investment and that those industries where intangible capital has risen the most are also those where the investment gap has grown larger in the last 10 years. Finally, I show that industries where intangibles grow fast are also associated with increasing market power.

Contents

1 Introduction

In recent years a growing concern has spread among economists about the sluggish pattern of investment in the aftermath of the global financial crisis ([23] Hall, 2015). Even most striking is the fact that investment has remained weak long time after the onset of the recovery ([1] Alexander and Eberly, 2016; [19] Gutierrez and Philippon, 2017). Several studies ([13] Crouzet and Eberly, 2019; [22] Gutierrez and Philippon, 2016) document the existence of such investment gap in the United States, defined as the residual difference between actual and "optimal" investment, after taking into account measures of future business opportunities available to firms. According to this literature, there are several explanations for the emergence of the gap: [13] Crouzet and Eberly (2019) in particular argue that the gap can be explained by the change in the composition of investment of American firms. Looking at physical capital investment could be misleading, because firms are investing an increasing proportion of their resources in assets that lack physical substance. Omitting intangible capital may hence overestimate the role of physical investment and translate into under-investment. An interesting feature of the "intangibles" hypothesis is that it can also contribute to explain other trends that economists have observed in the aggregate, such as the increase in market power and concentration across several industries and the increasing differences in productivity gains across firms and industries ([13] Crouzet and Eberly, 2019).

Because of data limitation, recent studies on the impact of intangible capital on investment and market power focus on the selection of companies that are listed in the stock exchange. The main goal of this analysis is instead to extend the current literature by considering the universe of Italian firms. This choice is motivated by two fundamental reasons: first of all, it is relevant to analyze whether an investment gap exists and determine its causes in a business and institutional context radically different from the US, including Antitrust enforcement and regulatory design ([29] Philippon, 2019). Second, the sample of firms used in this analysis is representative of the whole economy, not only of the firms that are listed in the stock-exchange. This group of firms accounts for a large share of the total economy value added in Italy and could be significantly different from the subsample of public firms, in terms of investment, markups and technological innovation. In principle, public firms are usually the largest and the most successful and may have a greater capacity to invest both in physical and intangible forms of capital: hence, I might expect the gap between actual and optimal investment to be larger when considering a sample that also includes small and medium businesses.

This paper is organized as follows: in the remaining part of this section I will define intangibles and discuss what features distinguish them from other capital. I will complement this part with the relationship between physical and intangible investment and clarify on the definition of the *investment gap*. Moreover, I will draw on the existing literature to explain why I can expect that industries which rely more heavily on intangibles are more likely to see a rise in the market power of the industry leaders. In Section 2, I summarize the main features of the dataset used in this analysis; in Section 3 some preliminary evidence is reported about the rise of intangibles in Italy and the evolution of different indicators for market power. Sections 4 and 5 report the econometric specifications used to answer the research questions and the estimates which are derived from those.

2 Literature review

2.1 The Rise of Intangibles

Industrialized countries are experiencing the transition towards a knowledge-based economy ([24] Haskel and Westlake, 2017): as the Services sector becomes more important in terms of its total contribution to global value added and Manufacturing relies more heavily on technological improvements in the production process, new forms of capital that often lack physical substance are becoming increasingly important. [11] Corrado and Hulten (2010) highlight that a major shift in the composition of investment and capital formation has happened, with almost one third of firms' total capital now amounting to intangible items.

A broad taxonomy of intangible capital has been proposed by [10] Corrado et al. (2005), who identify three broad groups:

- **Computerized information**, which includes software and database development. Broadly speaking, this category includes ICT systems which are used by firms to rationalize processes and improve decision marking: it is the case of Enterprise Resource Planning (ERP) and Consumer Relationship Management (CRM) sofware and of digitalized information stored into database. Especially software is likely to be capitalized into the balance sheet as an item in the intangible assets class.

- **Innovative property**: this category refers to all active Intellectual Property assets, such as patents and copyrights, which are most often recorded in the firms' balance sheet, as well as other forms of knowledge acquired through research efforts, which could be accessible through data about firm R&D expenditures.

- **Economic competencies**: this category includes all the knowledge which is embedded in the firm's human capital and it is specific to the line of business or the industry where the firm operates. This group also includes assets which are hardly recorded in the balance sheet, such as the value of a brand's name and the affection of the customer base. This class of items is the most difficult to capizalize in the balance sheet. Sometimes, however, these assets are recorded, for example in the case of an acquisition, when they would show up in the balance sheet under the voice of “Goodwill”.

As one can understand from the taxonomy, the definition of intangible capital is associated to many assets which in principle are very different from each-other. Still, they share some common characteristics, apart from the one of lacking physical substance. For example, intangible assets belonging to the first two groups are in general more easily and rapidly scalable than Property, Plant and Equipment (PPE): a piece of software can be replicated or used in new production lines at almost zero marginal cost, similarly to product or process innovations emerging from R&D activity. The fact that intangible assets are less excludable than PPE capital has strong implications for ownership and contractual relations: these items often require special forms of protection, such as patents or copyrights in order to avoid appropriation by potential competitors. Another characteristic of intangible capital is that it often cumulates in the form of up-front fixed investment. In [18] De Ridder (2021), intangibles are defined as inputs that decrease the marginal cost of those who adopt them, while at the same time endogenously rise the fixed cost at the industry level. In this framework, the adoption of intangible capital by a group of “leaders” can contribute to explain simultaneously the aggregate rise of the fixed cost, the decrease in productivity growth and the rise of markups.

There is another characteristic feature of intangible capital, namely the fact that firms are not equally good in riping the benefits of intangible investment: a large literature, following [7] Bloom et al. (2012), has highlighted that some firms are better than others at generating efficiency gains through the adoption of ICT technologies. For example, [30] Schivardi and Schmitz (2019) find that firms in Mediterranean countries are less productive than Northern European ones because they lack the managerial skills to take advantage of information technologies. Using the argument that intangible investment is firm-specific, because it relies on the specific human capital and knowledge embedded in a firm, [31] Weiss (2020) develops a dynamic model of firm investment that explains the rise of concentration and markups in the US economy. In his model, intangible capital is defined as being firm-specific: once firms invest in its formation, they cannot resell it to other firms and hence need to take into account a sunk cost when deciding whether to invest or not. Interestingly, this model manages to endogenize the rise in productivity dispersion that has been documented for the US economy by [5] Berlingieri et al. (2017) and [4] Autor et al. (2017). This large heterogeneity is documented also by [13] Crouzet and Eberly (2019) and imputed to the rise of intangibles: in the selected sample of public firms there are several that do not invest at all in intangible capital. Whether this heterogeneity at the firm level can explain the variance in firms’ return of investment, profitability and market power, both at the firm and industry level, is a still open question, which I will partially address in this paper.

2.2 Physical Capital Investment and Omitted Intangibles

One important consequence of the fact that intangibles are difficult to capitalize is that they are not easily recorded into National Accounts and are generally not taken into account for commonly used measures of Enterprise Value, such as Tobin's Q [8]. An emerging literature has developed around the possibility that the sluggish pattern of investment in the last decade can be explained by mis-measurment due to omission of intangible assets. If valuations do not take into account the value of intangible investment, they will overestimate the importance of physical capital: because of this bias, running a regression of firms' actual physical investment on the valuation and other controls will highlight a negative gap between observed investment and what the valuation predicts. The relationship between valuation measures and intangible capital has been analyzed empirically for the first time by [28] Peters and Taylor (2017): by trying to assess the predictive power of Tobin's Q on investment measures such as total investment and physical capital investment, they find that classic Q-theory performs better in industries that are characterized by a larger adoption rate of intangible capital. At the aggregate level, Tobin's Q seems to explain intangible investment way better than physical investment. By the same token, [22] Gutierrez and Philippon (2017) acknowledge that intangible mis-measurement is likely to explain, at least in part, the recent weakness of investment measures, relative to indicators of firm profitability and valuation.
If the gap emerges as a consequence of the omission of intangible investment, then it should be larger for those firms and industries that rely more heavily on intangible capital. Several studies have pointed out at the heterogeneity of investment trends across industries: in particular, [2] Alexander and Eberly (2018) document that the fall of physical investment in the aftermath of the financial crisis has been more marked in those sectors characterized by the largest shift of employment towards services and "cognitive skills", as defined by [3] Autor et al. (2010): in the sample of American firms, investment has remained strong in spatially-grounded industries, such as Energy and Mineral Extraction. In all sectors that exhibit skill-biased technological change, instead, the composition of investment shifts towards intangibles.

From a policy perspective, documenting whether firms are substituting physical capital with intangibles is a highly important issue: as pointed out by [13] Crouzet and Eberly (2019), intangible assets differ from physical ones because they are less interest-sensitive (because of higher depreciation rates) and because they are more difficult to use as collateral. For both reasons, monetary policy is a less effective tool for stimulating intangible investment, because interest rates may be less sensitive to monetary interventions, compared to the case of physical capital: more appropriate policies might consist in property rights enforcement and market-development, including efforts to improve the measurement and accounting standards used to measure the intangible capital stock.

2.3 The link between Intangibles and Market Structure

As mentioned before, [18] De Ridder (2021) reconnects the recent rise of aggregate markups in the US to the transition towards a more intangible-intensive economy. Scalability of intangible inputs ensures that early adopters of intangible technology can rapidly increase their market shares by progressively reducing their marginal cost; on the other hand, the fact that intangible assets are often capitalized in the form of property rights makes it more difficult for those who have not initially invested to catch up with the leaders, consolidating the dominant position of the latter. On the same line, [31] Weiss (2020) calibrates a dynamic model of monopolistic competition in which firms can make a one-time fixed investment in intangibles: he shows that the rise in intangible capital documented in the US from 2000 onwards can explain more than half of the increases in concentration and markups. In both models, the mechanism connecting markups and concentration to intangibles is the rise of fixed costs for new entrants and the progressive reallocation of market shares to those firms that have performed productivity-enhancing intangible investments.

A larger debate has developed around the issue of which one of the two forces matters the most: [4] Autor et al. (2020), for example, regard intangible adoption as efficiency-enhancing and hence relate the rising concentration documented in the US economy to the emergence of "Superstar firms" that are more productive than others; [16] De Loecker and Eeckhout (2020) and [21] Gutierrez and Philippon (2018) claim that the rise in concentration couples with rising markups, emphasising the fact that intangible assets may help incumbents to deter competitors, hence conferring considerable market power to industry leaders. [13] Crouzet and Eberly (2019) provide evidence that the link between intangible adoption, market power, concentration and productivity gains varies widely across sectors: using data about US public companies, they show that, while in the Consumer Retail sector measures of intangible intensity are highly correlated with rising productivity gains and concentration, but not with market power, in other industries such as Manufacturing and the High-tech sector a strong rise of markups has coupled the one of concentration and productivity. This heterogeneity could be motivated by the distinct function of intangible capital in different industries: for example, in the Automotive industry intangibles are mostly patents or trademarks and they reasonably contribute to the rise of barriers against potential competitors; conversely, in the retail sector, intangible investment might consist in the development of digital infrastructure and other technical improvements that increase the productivity of production and distribution processes, without necessarily rising entry barriers.

3 Data and Measurement

3.1 Data Sources

Differently from the past literature, that examined the impact of intangible capital in the subset of public firms, I am going to exploit a unique dataset containing information about the universe of Italian firms (including those that are privately-held). The exercise is relevant, especially in the context of the Italian economy, where the population of firms that are listed is a relatively small sub-sample: the total capitalization of non-financial firms accounts for 20% of the real economy, against around 40% in other industrialized European countries ([20] Finaldi et al., 2020).
The first data source I use is CERVED,[1] which gives me access to balance-sheet information on a sample of limited liability firms. The final sample is representative of the Italian economy, including both listed and unlisted firms. In principle, I have data on all active businesses in the time-span 2000 - 2020. I will use the full sample to perform a descriptive analysis of the long-term trends in investment rates, markups, market concentration and intangible intensity. Instead, the sample period in the multivariate empirical analysis will range between 2011 and 2019. The reason is that CERVED does not provide me with a direct measure of enterprise value such as Average Tobin's Q, as in the case of [13] Crouzet and Eberly (2019).
I therefore rely on industry-specific valuation measures contained in Aswath Damodaran's website,[2] which are available from 2011 onwards.
The use of Aswath Damodaran's industry-specific valuation measures means that my approach to determine firms' value relies on multiples based on the assumption that similar firms have comparable financial metrics [26] (Liu, 2002). Hence, in order to proxy for Enterprise Value(EV), I use the *EV/Invested Capital* multiple from Damodaran's website.

The third data source that I have employed in my analysis is the AIDA (Analisi Informatizzata delle Aziende Italiane) dataset, containing information about around one million Italian firms (those that are mandated to turn-in their balance sheet). Using information from AIDA, my analysis focuses on the sample of public firms. The reason is that AIDA gives me access to information on firms' valuation, and therefore I will be able to directly compare my results to what Crouzet-Eberly find in the sample of US public firms. I will then refer to CERVED in order to derive analogous results in the "universal" sample. The results obtained with the AIDA dataset are reported in the Appendix.

[1] CERVED is the greatest information provider about Italian business enterprises: "https://www.cerved.com/"
[2] Measures about industry level multiples for European firms are available at "https://pages.stern.nyu.edu/adamodar/"

3.2 Firm Balance-sheet Variables

In the following section I am going to describe the construction of the main variables used throughout my analysis. Assuming that each firm has two different types of assets, tangible and intangible, respectively K^τ and K^ι, with depreciation rates δ^τ and δ^ι, I define the physical capital investment rate as the ratio of CAPEX computed for physical capital over the physical capital stock at the end of the period. Namely, the physical investment rate for firm i in industry j at time t is:

$$I^\tau_{ijt} = \frac{CAPEX^\tau_{ijt}}{K^\tau_{ijt}} = \frac{K^\tau_{ijt} - K^\tau_{ijt-1} + \delta^\tau_{ijt}}{K^\tau_{ijt}}. \tag{1}$$

This will be my main dependent variable throughout my analysis. As I will explain in later Sections, I will also perform robustness checks using a version of this variable that, instead of CAPEX, uses a CERVED provided measure of investment expenditures in the numerator.

I also generate a measure of the "total investment rate", defined as the ratio of total firm investments in year t over the overall capital stock (tangible and intangible) in the same year.

$$I^{tot}_{ijt} = \frac{CAPEX^\tau_{ijt} + CAPEX^\iota_{ijt}}{K^\tau_{ijt} + K^\iota_{ijt}} = \frac{K^\tau_{ijt} - K^\tau_{ijt-1} + \delta^\tau_{ijt} + K^\iota_{ijt} - K^\iota_{ijt-1} + \delta^\iota_{ijt}}{K^\tau_{ijt} + K^\iota_{ijt}}. \tag{2}$$

These two ratios (I^τ_{ijt} and I^{tot}_{ijt}) can be interpreted as measures of the investment-intensity of a firm, meaning what percentage of a company's physical/total capital is devoted to the acquisition of new assets or to offsetting depreciation. I also construct the intangible intensity of each firm, defined as the percentage of the firm's intangible assets over total capital

$$s^\iota_{ijt} = \frac{K^\iota_{ijt}}{K^\tau_{ijt} + K^\iota_{ijt}}. \tag{3}$$

Last, I will use firm-level variables directly available in the reference datasets such as $ValueAdded_{ijt}$, $EBIT_{ijt}$, $\frac{EBIT_{ijt}}{K^\tau_{ijt}}$ or $\frac{EBIT_{ijt}}{K^\tau_{ijt}+K^\iota}$, which will allow me to control for size and cash flow. Table 1 summarizes the main characteristics of the variables described in this section for the two reference dataset (CERVED and AIDA). The table shows that there is a trade-off between sample numerosity and availability of valuation measures. Given the small sample size, I will use AIDA to perform robustness checks and compare my findigs with the ones in Crouzet-Eberly. The rest of the analysis to follow will be based on CERVED data, that are more granular and allow me to investigate investment and markup trends also for Italian small and medium enterprises.

	CERVED Data			
	count	mean	median	sd
Phy. inv. rate	2555937	.2084326	.0722892	.3269096
Tot. inv. rate	2418434	.0471216	.1171171	.8129064
Intangible Share	3122799	.2530463	.0605892	.3378352
Cash Flow	2906260	2.290682	.5163934	127.9601
N	3,551,313			

	AIDA Data			
	count	mean	median	sd
Phy. inv. rate	2811	.2228289	.1598954	.512781
Intangible share	2861	.443215	.5541255	.3767127
log Cash Flow	2064	10.20347	7.177019	9.614638
N	3,136			

Table 1: Summary Statistics for Firm Balance Sheet Variables

3.3 Concentration Measures

My main measure of concentration at the industry level is the Herfindahl–Hirschman Index (HHI):

$$HHI_j = \Sigma_i ms_{ij}^2 \tag{4}$$

where ms_{ij}^2 is the squared market share of firm i in industry j. The index ranges from 0 to 1, with 1 indicating monopoly power.

3.4 Markup Measurement

Since in the last section of the paper I am going to investigate the relation between markups and intangible intensity at the industry level, I will now summarize the main steps in the computation of markups. My approach is to compute markups at the firm level using the methodology developed by [17] De Loecker and Warzynski (2012) and then average the numbers at the industry level in order to obtain aggregate figures.
This methodology builds on production function estimation in order to retrieve the elasticity of production to a variable input X_{it} (labor in my case), and then uses the elasticity to compute the markup at the firm level. The theoretical foundation of this approach is explained in detail with a stylized model of firm-level markups, reported in the Appendix.

In practice, I obtain the elasticity of output to labor by estimating the production function for each sector of the economy via the [27] Olley and Pakes procedure (Olley and Pakes, 1996). Then, I compute the firm-level markup as the estimated elasticity times the ratio of Value-added to the

Industries	(1) Labor Elasticity	(2) Capital Elasticity
Energy	0.689***	0.066***
	(0.00373)	(0.00999)
Hotel and Restaurant	0.750***	0.0471***
	(0.00183)	(0.00305)
Manufacturing	0.793***	0.066***
	(0.0004)	(0.00393)
Mineral extraction	0.832***	0.441***
	(0.1103)	(0.1386)
Services	0.7703***	0.0463***
	(0.00217)	(0.00153)
Transport storage and comm.	0.7359***	0.077***
	(0.00181)	(0.00185)
Wholesale and retail trade	0.7331***	0.0564***
	(0.00155)	(0.00748)

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Elasticity estimates - OP production function estimation

Cost of Labor. Table 2 reports my estimates of the labor elasticity α^X, obtained at the level of the 7 major sectors of the economy via O-P production function estimation.

4 Descriptive Analysis

In what follows, I am going to report descriptive statistics of the main variable of interests and discuss preliminary evidence about the evolution of the intangible share, investment rates, concentration and markups.

4.1 Weak Investment

Figure 1 reports the declining trend in physical capital investment I_t^τ in the CERVED sample, for the last 20 years. My main measures of the capital stock in the sample are the variables "Intangible Assets *(Immobilizzazioni immateriali)*" and "Tangible Assets *(Immobilizzazioni materiali)*", on which I have information at the firm level. Since I also have information about the depreciation rates of both types of capital for each firm, I can compute CAPEX and the physical investment rate as in (1). The trend is sharply declining, with physical capital investment halving over the 20-year span I consider. By comparing the average trend with the one weighted by Value Added, it also appears that those firms that matter the most in terms of Value-added are those whose physical investment has been weaker. These results closely track the ones obtained by Crouzet and Eberly for the US. In the US case, the weakness of investment was more pronounced in some sectors, particulary those that were more exposed to trade penetration from China and to technological progress. Interestingly in the Italian case the pattern is consistent to the aggregate figures in all sectors of the economy. Sectoral trends are portrayed in Figure A1 in the Appendix.

4.2 The Rise of Intangibles

While physical investment appears to be waning, other forms of capital have gained importance during the same time horizon. Figure 2 reports the evolution of the aggregate intangible share s_{ijt}^ι as defined in the previous section. Also in this case, the trend is sharper when I aggregate industries by taking into consideration their Value-added contribution, meaning that the rise of intangibles has been more marked for those firms that account for a larger share of the economy. On the other hand, the overall level of intangible intensity is constant in the aggregate economy if I simply aggregate by taking the average of the individual shares ($\sum_i \sum_j s_{ijt}$).[3]

In Figure 3, I plot the distribution of intangible investments across the years in my sample period. One interesting feature of my firm-level measure of intangible intensity is that the its distribution across all firms in the economy is bimodal, with one mode around zero and one at a higher value of intangible intensity. If I dis-aggregate the figure at the sector level, heterogeneity in the distribution

[3] Figure A2 portrays the trend in the levels of intangible intensity across the 5 largest sectors of the economy. The main message contained in the figure is that, while all industries witness a rising trend in the take-up of intangible inputs, the overall level of intangible intensity is very heterogeneous: this ranges from 30% for Services to less than 20% in the Energy sector and in Manufacturing.

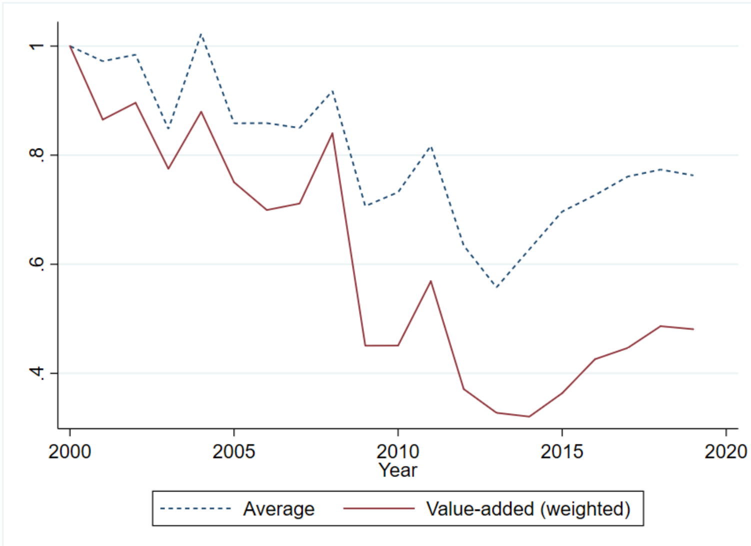

Figure 1: The figure reports the trend of aggregate physical capital investment I^{τ} in the time-span 2000 - 2019. The blue line reports the arithmetic average across all firms in the economy, while the red one weights each firm according to its contribution to the total industry Value Added. Both indices take 2000 as a baseline year and plot the ratio of aggregate investment with respect to the baseline.

Figure 2: The figure reports the trend of the aggregate intangible capital share s_t in the time-span 2000 - 2019. The blue dashed line reports the arithmetic average across all firms in the economy, while the red weights each firm by its Value-added contribution. The year 2000 is taken as a baseline.

of intangibles at the industry level becomes apparent.

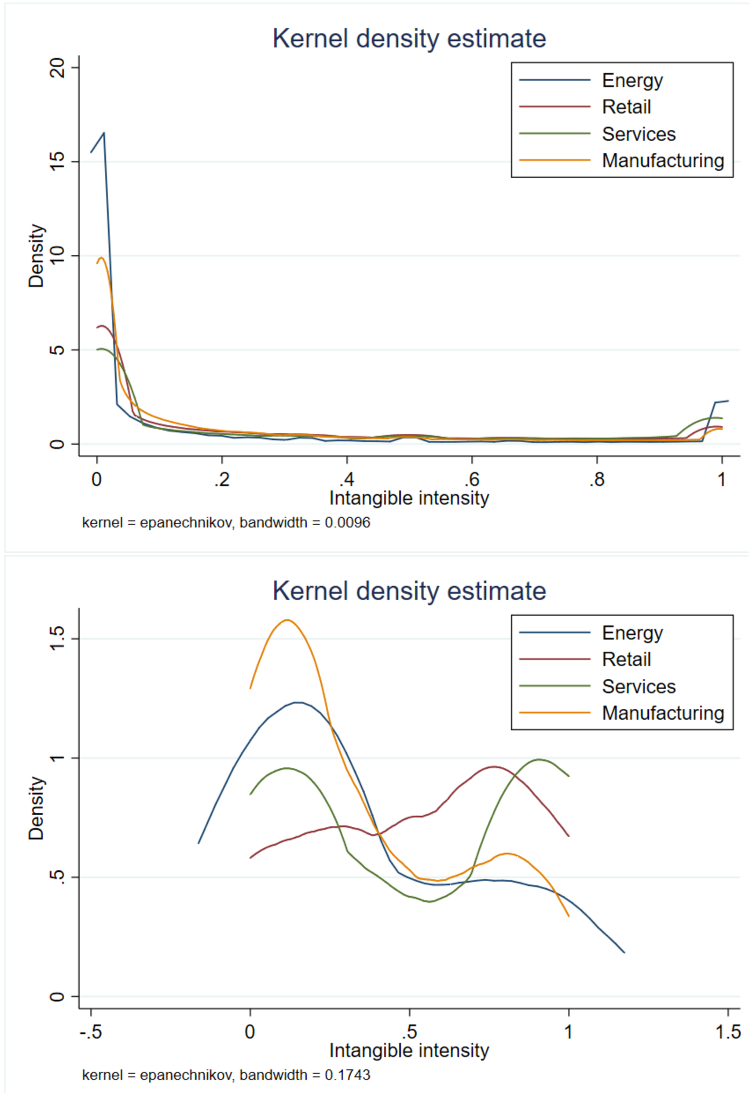

Figure 3: Distribution of the sector-level intangible share s_{jt}, in the CERVED and AIDA sample respectively, in year 2019

Just inspecting the trend in investment and in the adoption of intangible balance-sheet items is not enough to answer the question of whether such a decline in physical investment is due to the transition of the economy towards intangible capital. To do so, I will turn to a framework in which I can control for other reasons that can potentially explain firms' slow-down in investment.

For example, it is possible that firms turned away from investment because there are less business opportunities in the economy, or because firms that have consolidated their position as market leaders have a lower incentive to invest with respect to new-entrants.

4.3 Market Power

As in Crouzet and Eberly, I rely on mainly two indicators of market power: market concentration, measured by the HHI index and markups.
Figure 4 reports the main estimates about the evolution of market concentration in Italy. Market Concentration is measured using the HHI index, as defined in equation (4). My definition of a market corresponds to the first 4-digits ATECO-2002 industry classification. As shown in the figure, there is no clear trend in the HHI index, at least by looking at the arithmetic average across industries: if I report a measure of the HHI which takes into account the Value-added contribution of each firm, it is more evident that there has been an increase in concentration in the last 10 years with respect to year 2000.

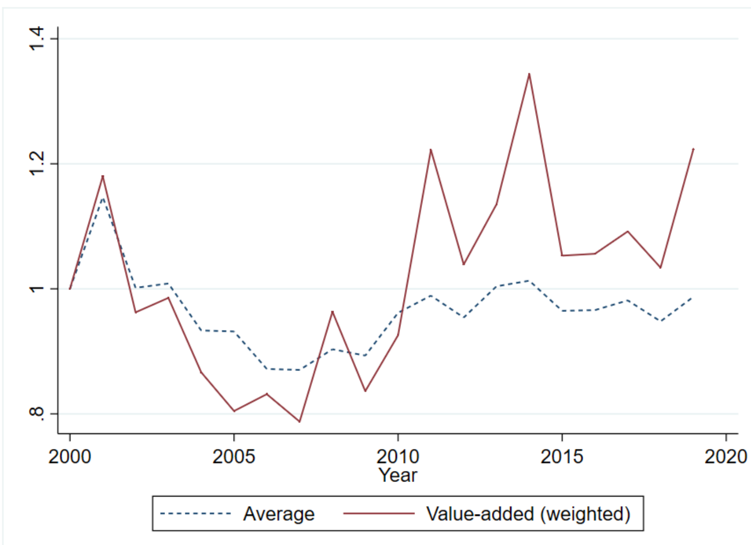

Figure 4: Evolution of the HHI index, normalized to its level in the year 2000

Figure 5 reports the main findings about the evolution of aggregate markups in the Italian economy during the last 20 years. The figure plots different percentiles of the markup distribution and the mean. The trend is overall declining, with large declines in the early 2000s and after the global financial crisis and with a flattening trend afterwards.

This evidence is contrasting with the results in [13] Crouzet-Eberly (2019), but could be driven by the fact that, while Crouzet-Eberly only compute the markups for the selected sample of public

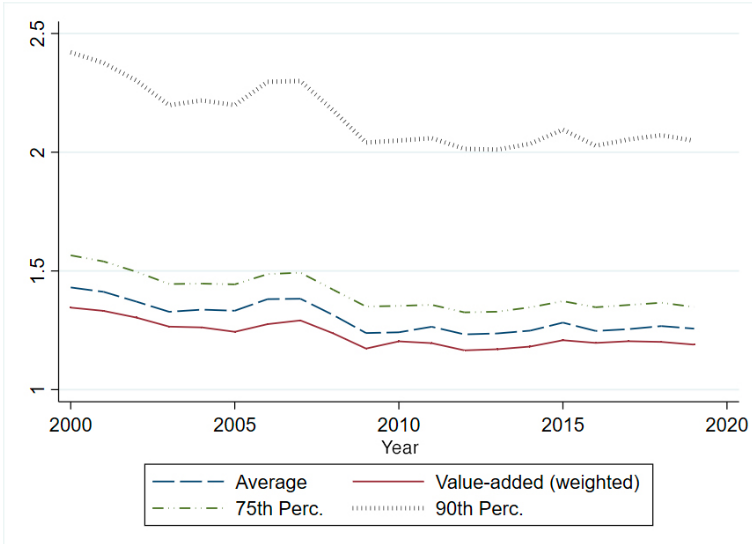

Figure 5: Evolution of different percentiles of the markup markup distribution in the Italian economy

firms, I am reporting aggregate markups for a sample representative of the universe of Italian firms, including many small and medium enterprises. Differences could also be due by the fact that I use the cost of labor as a variable input in the markup formula specified in (5): since labor is not a perfectly flexible input, this could partially bias my estimates because firms cannot perfectly adjust in every time period.
The evidence on markups is corroborated by the fact that, if I look at the overall markup distribution, this has progressively been characterized by lower density of high-markup firms (Figure 6).

Consistently with the results of [9] Ciapanna et al. (2022), the discrepancy in findings between my analysis and the US case is likely to be driven by difference in the elasticity estimates between Italy and the US and by the different sample of firms considered in the analysis of US firms . Also when analyzing trends at the sectoral level (Figure A3) there are remarkable differences with the US case: even if markups seems to decrease in all industries, there is large sectoral heterogeneity in the steepness of the trend, with the largest decrease in Services and in Wholesale and Retail Trade.

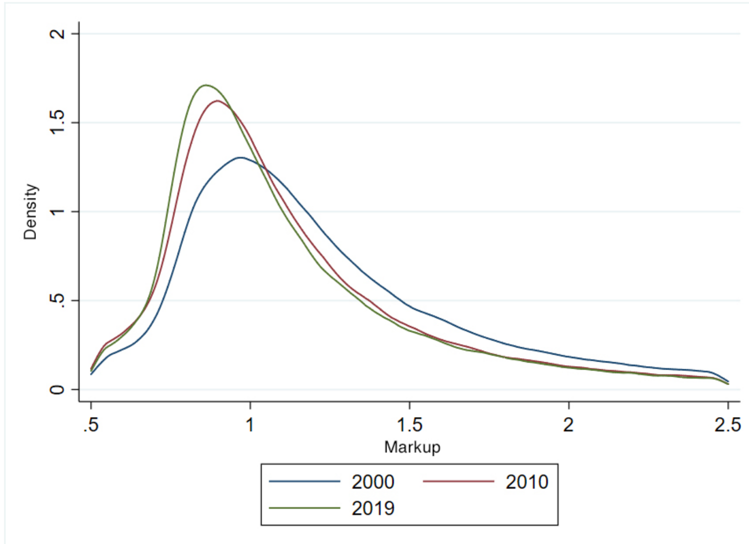

Figure 6: Evolution of the aggregate distribution of markups at the firm level.

5 Multivariate Analysis: Investment Gap

This section is devoted to the discussion of the empirical models that I am going to use in order to investigate the relationship between investment and intangible capital. First, I define the concept of investment gap, then I introduce the main empirical specification used for its estimation. Later, I will discuss my results and analyze the correlation between the investment gap and intangible intensity at the industry level. All the results will use the sample of CERVED firms, while results using AIDA are in the Appendix.

5.1 Defining the Investment Gap: Empirical specification

Following the predictions of the theoretical model of firm investment developed by [13] Crouzet and Eberly (2019) - which I derive in the Appendix - I am going to investigate whether there is evidence of declining physical capital investment for Italian firms, and whether this trend can be explained by the omission of an important factor such as intangible capital. I am going to estimate the following structural equation:

$$i^{\tau}_{ijt} = \alpha_i + \gamma_t + \delta Q_{jt-1} + \beta' X_{ijt-1} + \epsilon_{ijt}. \tag{5}$$

In practice, I regress the physical capital investment measure i^{τ}_{ijt} on lagged average physical Q (on which I have information at the industry-level) and a set of firm level variables (size and cash-flow of each firm). Given the panel structure of the dataset, I include firm fixed effects and time fixed effects: the first allow me to control for time invariant endogeneity at the firm level, the second provide an estimate of the average discrepancy between the investment measures and average physical Q in a particular industry. I call the estimate of the time effect $\hat{\gamma}_t$ **investment gap**: if firms do not match the level of investment predicted by industry-level valuations, the estimate $\hat{\gamma}_t$ will be negative and significantly different from zero. Hence, if the trend of $\hat{\gamma}_t$ is negative and declining over time, I will interpret this as evidence of the existence of a gap between valuation measures and actual physical investment. Importantly, my estimate of the gap is not informative about the absolute *level* of investment, but rather about the trend of physical capital investments with respect to a reference year, which in my case is 2012.

As also highlighted by [13] Crouzet and Eberly (2019), the gap is expected to be wider in those industries that are more intangible-intensive: then, I should expect that the industry-level time effects estimates $\hat{\gamma}_{jt}$ will be more negative and decreasing exactly in the industries where the industry-level intangible share s_{jt} is larger. This can be detected by looking at the correlation between the average trend in the gap for each industry and the industry-average intangible intensity. Moreover, since I consider the gap to be originated by the omission of intangible capital, I should expect it to become wider in those industries which over the sample period have witnessed the largest growth in intangible capital intensity. This correlation will be investigated by running separate regressions as in (7) for each industry, in order to obtain industry-level estimates of $\hat{\gamma}_t$, and then by running the following specification on a second stage:

$$\gamma_{jt} = \alpha_j + \lambda_t + \xi s^{\iota}_{jt} + \epsilon_{ijt} \tag{6}$$

where α_j is an industry-fixed effect which will capture time-invariant endogeneity for each industry, λ_t is a time-fixed effect, controlling for aggregate shifts to the industry-level trend of investment, s^{ι}_{jt} is the average intangible intensity of firms in industry j at time t. I expect the coefficient associated with intangible intensity to be negative and significantly different from 0, meaning that those industries that witnessed a steeper growth of the intangible share of total assets are associated with a larger physical investment decline.

5.2 Aggregate Evidence

Figure 7 reports the estimates of the investment gap trend for the aggregate CERVED sample. The trend is negative, with the yearly investment rate always below its original level in 2012. The gap seems to narrow starting from the year 2014 until 2017, but opens up further in more recent years. In terms of magnitude, this result is economically significant: the estimates suggest that in 2019, the physical investment rate for the average firm in the economy was 6 percentage points lower than 2012 (considering that the mean physical investment rate in 2012 is 0.18, this implies a 33% reduction in average physical investment from 2012 to 2019). Figure 7 also compares two different measures of the gap, which are different in the variable which has been used as the dependent variable in specification (7). The plain line reports the investment gap trend under my main measure of physical investment rate, while the dashed line uses the CERVED investment expenditure measure. Overall, the trends are similar, with the exception that the CERVED measure displays a reduction in the gap during the years 2016 and 2017. Regression estimates for specification (7) are also reported numerically in Table A1 in the Appendix.

5.3 Industry-level Evidence

To analyze whether the results are driven by a sub-group of firms in my sample, or are a common feature among all firms, I estimate a modified version of specification 7:

$$i^{\tau}_{ijt} = \alpha_i + \eta_j + \gamma_{jt} + \delta Q_{jt-1} + \beta' X_{ijt-1} + \epsilon_{ijt} \tag{7}$$

Here, I include an industry fixed effect controlling for time invariant characteristics of each industry j and estimate the time trend for each industry. In this case, the estimated trend will capture the investment gap for each industry, and I expect it to be larger and more declining for those industries that have witnessed the fastest growth of intangibles. My estimates are displayed in Figure 8: overall, the investment gap is negative and declining in trend across almost all industries in the years between 2015 and 2017, with the exception of the Transport and Communications sector. Interestingly, the declining trend is steeper in the Energy sector, in Services and in the Wholesale and Retail sector. This strengthens the prior expectation that the gap should be more pronounced in those sectors of the economy that rely the most heavily on intangible capital. This hypothesis will be further inspected in the last part of the section, in which I will discuss the relationship between intangible intensity and the investment gap by running specification (8) at narrower aggregation level.

Overall, the results suggest that there is wide industry heterogeneity in investment patterns and in the way in which valuations map into physical investment. This is true also when I do not look at the trend: Table 1 reports the industry fixed effect estimate η_j from specification (9). This shows that different industries start from levels of mismatch which are quite distinct. For instance, the Manufacturing sector starts from the lowest level overall, but with a less declining trend.

5.4 Using Total Investment as Dependent Variable

To check the robustness of my results, I repeat the main analysis using as a dependent variable a measure of investment that does not only look at physical capital. According to the model developed by Crouzet and Eberly, if the bias in specification (7) arises because valuation measures overestimate

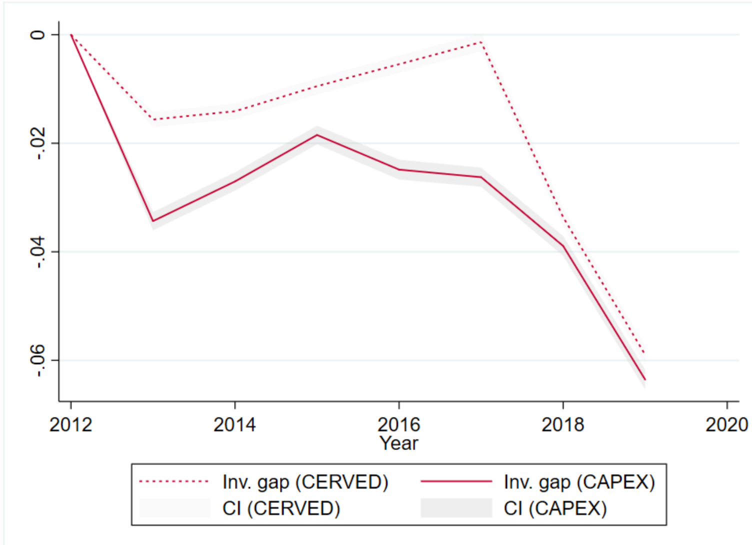

Figure 7: The figure plots the evolution of the investment gap for the firms of the CERVED sample, using two different measures for the investment rate i_t^τ: my main measure (plain line) is the ratio of CAPEX expenditures in phyiscal capital over the physical capital stock for firm i at time t; as a robustness check, I also use a measure of investment directly available on the CERVED dataset (scattered line), which considers physical investment expenditures by firms, rather than looking at the change in the accounting capital figures net of depreciation.

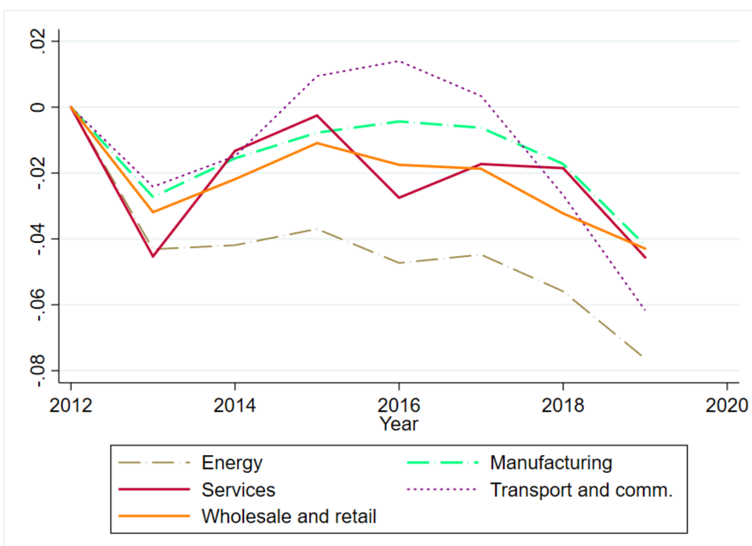

Figure 8: The investment gap in the 5 largest sectors of the economy

VARIABLES	(1) Physical Investment Rate
Hotel and Restaurant	-0.0128
	(0.0104)
Manufacturing	-0.0381***
	(0.00672)
Services	-0.00187
	(0.0113)
Transport comm.	-0.0312**
	(0.0147)
Wholesale and retail	-0.0251***
	(0.00802)
Observations	2,015,635
R-squared	0.340

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Industry fixed effects estimates, in deviation from the level in the Energy sector

the incentive to invest in physical capital, looking at an aggregate measure of investment should at least attenuate the bias. Figure 9 reports the estimates of the investment gap when I use a measure of *total investment rate*, defined as $i_t^{tot} = \frac{CAPEX_t^{\tau} + CAPEX_t^{\iota}}{K_t^{\tau} + K_t^{\iota}}$. As shown in Figure 9, the trend is not anymore declining when I use a measure of total investment as my dependent variable, with an initial gap in the years 2012 - 2014, and an actual boost of investment in the following period. The fact that there is a gap in the first 3 years of the sample period could be explained by the fact that some external factor, such as the sovereign debt crisis of 2011-2012, actually pushed firms to under-invest with respect to what valuations would predict. In general, the picture provides evidence that, during the last decade, Italian firms have shifted from investing in physical capital towards forms of intangible investment. Moreover, this result supports the hypothesis that valuation measures based on average or total Q overestimate the incentive to invest in physical capital and hence contributes to associate the investment gap that has been documented in Figure 1 with the partial substitution of physical capital with intangibles.

5.5 The Relationship between Intangible Intensity and the Investment Gap

In order to deepen my understanding about the relationship between intangible capital and the investment gap, I average these two variables at a smaller level of aggregation, namely the one corresponding to the first three digits of the ATECO classification[4]. In this way, I cluster the whole

[4]ATECO is the Italian equivalent of the NACE classification of economic activities

VARIABLES	(1) Inv. Gap	(2) Inv. Gap	(3) Inv. Gap	(4) Inv. Gap
Intangible Intensity	-0.0920***	-0.104***	-0.110***	-0.129***
	(0.0304)	(0.0284)	(0.0330)	(0.0289)
Year FE	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes
Observations	312	312	312	312
R-squared	0.037	0.136	0.218	0.319

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimated coefficients in a regressions of the industry-level investment gap on the industry-average intangible intensity

economy into 96 industries (corresponding to the number of distinct ATECO codes that I have in my sample). For each of these, I compute the average intangible share in year t and the average gap in the same year. Figure 10 below plots the simple correlation between the two averages: as shown in the picture, there is evidence of a weak negative relationship between intangible intensity and the investment gap, suggesting that the gap is wider in those industries where intangibles play a bigger role. The simple Pearson correlation coefficient between the two variables is -0.218, significant at the 1% level: taking into account the spread of intangible intensity, this means that a one-standard deviation increase in intangible intensity is associated with a 2% decrease of the investment rate.

I then estimate specification (8) including industry FE and time FE, which absorb the effect of time invariant industry heterogeneity and of aggregate time shocks. By regressing the industry-level investment gap on the industry-average intangible intensity, I expect the gap to widen for those industries that experimented the largest rise in intangible capital. It is important to note that my specification is potentially exposed to endogeneity problems arising because of possible omitted factors that affect at the same time the intangible intensity of an industry and the investment gap. For this reason, I will stick to interpreting my results as evidence of a simple correlation, without claiming causality. The estimates are reported in Table 4: the coefficient associated with intangible intensity is always negative and significantly different from 0. It increases in magnitude as I progressively add year and industry FE, suggesting that the bias on the Intangible Intensity coefficient has an upward direction. In the specification with both types of FE, the coefficient associated to intangible intensity is -0.129: this implies that moving from and industry at the 25th percentile of the intangible share distribution to the 75th causes an increase of the gap of about 1.3 percentage points. The number is economically significant, since it accounts for about one third of the gap in 2013 and 15% of the gap in 2019.

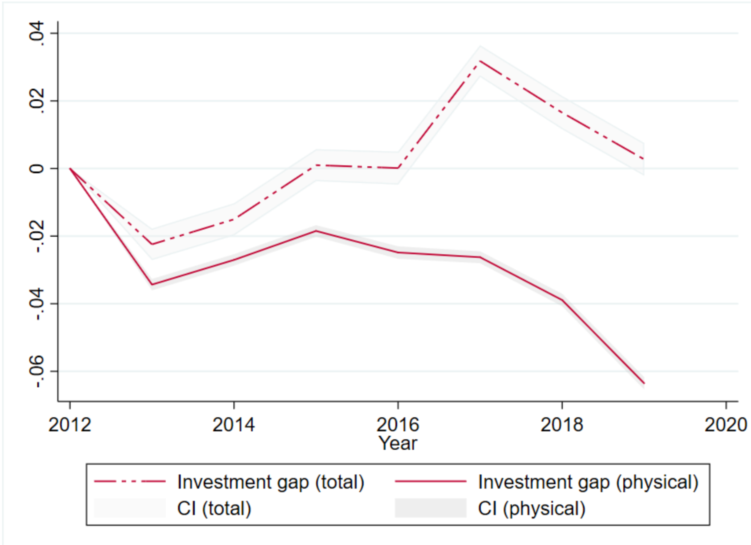

Figure 9: The investment gap estimated using the physical capital investment rate (solid line) and the total capital investment rate (dashed line).

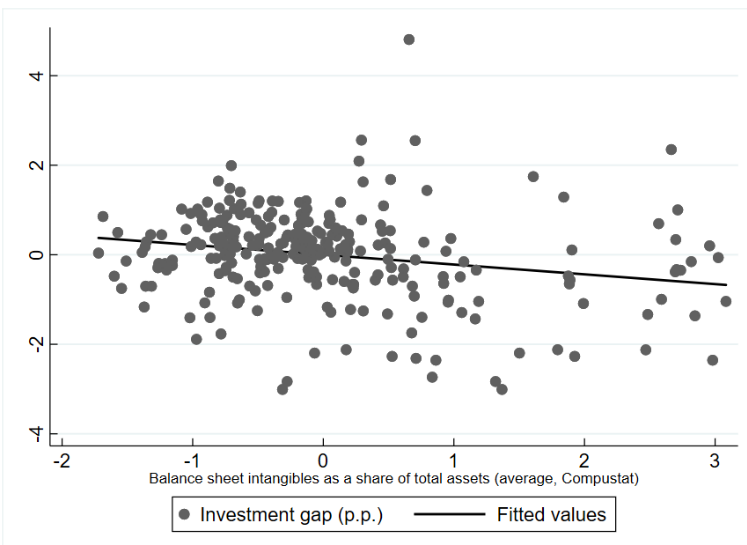

Figure 10: Industry-level correlation between average intangible share and the investment gap. For both variables, observation values are normalized with respect to the cross-sectional mean

VARIABLES	(1) Inv. Gap	(2) Inv. Gap	(3) Inv. Gap	(4) Inv. Gap
Intangible/VA(*)	-0.00224	-0.00224	-0.366***	-0.342***
	(0.0656)	(0.0656)	(0.125)	(0.110)
Year FE	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes
Observations	312	312	312	312
R-squared	0.000	0.000	0.471	0.555
Lag. Int.(**)	-0.115***	-0.126***	-0.134***	-0.151***
	(0.0352)	(0.0331)	(0.0387)	(0.0345)
Year FE	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes
Observations	312	312	312	312
R-squared	0.045	0.142	0.223	0.322

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Estimated coefficients in a regressions of the industry-level investment gap on the industry-average intangible intensity, defines as (*) the average of the intangible stock over Value added and as (**) the lagged value of intangible intensity

5.5.1 Investment Gap: Robustness Analysis

One important concern about specifications (7) and (8) is that both my dependent variable, the physical capital investment rate i^{ι}_{ijt} and the intangible intensity measure s^{ι}_{ijt} depend on the physical capital stock K^{τ}. The risk is that the two variables are mechanically negatively correlated, because those industries that in the first place experience more sluggish physical capital intensity will also be more intangible intensity by construction. I tackle this "reverse causality" in two ways: first, I change my measure of intangible intensity, using a variable that, by construction, does not depend on physical capital. Specifically, I will use the industry average of the firm intangible capital to Value-added ratio $\tilde{s_{ijt}} = \frac{K^{\iota}_{ijt}}{VA_{ijt}}$; second, I repeat the empirical analysis using the lagged value of the balance-sheet intangible-share, under the assumption that causal links cannot move from investment at time t towards the intangible share at time $t-1$, while the opposite is potentially true. The results are reported in Table 5: overall, the evidence of a negative correlation is robust to the alternative measures that I have identified and seems to point in the same direction as the original specification, with actually larger magnitude when I use the Value Added-based measure: there, moving from the 25th to the 75th percentile of the intangible distribution comes with an increase in the gap of about 1.7 percentage points.

5.5.2 Measurement Error Correction

A second threat to the interpretation of my results is that the estimates could be biased because of some error in the measurement of intangible capital by firms. Intangible capital is by nature less collateralizable and encompasses different asset classes, with no clear indication of what firms should report in the balance sheet: this makes it more difficult to measure with respect to "traditional" physical capital and hence calls for a robustness check in order to assess the goodness of the estimates obtained in the previous sections. For example, one potentially "noisy" component of balance-sheet intangible capital accounts is Goodwill[5], an item which is only registered in the event of an acquisition.

To address this issue, I instrument my measure of intangible share with several variables that should correlate at the industry level. The purpose of this exercise is not to extrapolate causal links between intangibles and my main dependent variables, as in traditional IV, but rather to isolate the variation in the intangible share across industries in order to correct for potential bias caused by measurement error. My chosen instruments are obtained from ISTAT[6], in particular from the dataset on ICT adoption among Italian firms. I will use information on the adoption of digital software and ICT infrastructure by firms which is likely to be orthogonal to Goodwill, but should correlate with intangible assets related to RD intensity and software adoption. In summary, in the first stage I instrument the intangible capital share at the industry level with the industry-average information obtained from ISTAT, and then regress the investment gap on the instrumented intangible share in the second stage. Results from this exercise are reported in Table 6.

As shown in the table, the sign of the instrumented coefficient is always negative, confirming my intuition that those industries that have become more intangible intensive are also characterized by a widening investment gap. The coefficient is only significant when I use as an instrument the proportion of firms adopting ERP software[7] in their production facility in the same year and when I use average software adoption. All other instruments do not achieve 10% statistical significance. The first stage F-test is always below 10, indicating weak instruments. Even if this is not a concern, since I am not using IV in order to assess causal links, it indicates that the chosen instruments only correlate with a small portion of the overall variance of the CERVED balance-sheet measure of intangible share. This is natural, given that balance-sheet intangibles comprehend several assets, very different from each other.

[5] Goodwill is an intangible asset that accounts for the excess purchase of another company: hence, this measure is affected by the value of a brand and its reputation It is calculated by subtracting to the transaction price the value of the assets and liabilities of the target firm

[6] ISTAT is the main statistical agency of the Italian government: http://dati.istat.it/Index.aspx

[7] Enterprise Resource Planning software is a type of sofware that integrates all the basic functions of a firm - sales, procurement, inventories - in order to support managers in their decision-making process

VARIABLES	(1) Inv.Gap	(2) Inv.Gap	(3) Inv.Gap	(4) Inv.Gap	(5) Inv.Gap
Int. Share	-0.372*	-0.420	-0.393*	-1.524	-0.136
	(0.201)	(0.220)	(0.220)	(0.899)	(3.68)
Instruments	ERP	CRM	Avg.	Online	RD
F-stat (1st stg)	9.26	1.77	8.94	0.17	15.13
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	273	273	273	310	272

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: IV regressions of the investment gap on the industry-level intangible share. Each column corresponds to the regression using a different instrument, respectively the proportion of firms in each industry using ERP software,using CRM software with marketing purposes, average ERP and CRM adoption, the proportion of firms doing online sales, the industry-average level of RD expenditure. All data about the instruments come from the ISTAT website.

6 Empirical Analysis: Market Power

Next, I investigate what is the impact of intangible capital on market power: as I have mentioned in the introduction, intangible capital may raise industry barriers, decreasing leaders' marginal cost and at the same time increasing entry sunk costs. My main measure of market power are markups, which I defined in Section 2, equation (6) as the ratio of price margins over the marginal cost of a firm. This measure does not allow to quantify the power that leaders have in terms of deterring potential entrants, but rather considers the final welfare cost generated by those industries leaders who can increase the price with respect to the marginal cost.

In this section, I use computed markups to analyze the correlation between markups and intangibles at the industry level. To my knowledge, this is the first study that tries to assess this relationship in the case of Italy and using a sample of firms which is representative of the whole economy. In the Appendix, I repeat the analysis using concentration as an alternative measure of market power. The results obtained using concentration are however to be considered with caution, since the relationship between concentration and market power is an ambiguous one ([12] Covarrubias et al, 2020). In the case of intangibles, for example, one possibility is that new technologies improve the efficiency of those who benefit of their productivity enhancements, making sales more concentrated in a given industry, but at the same time without a substantial change of the competitive structure: in this case, intangible intensity would be positively correlated with concentration but this would not necessarily imply a shift in market power.

6.1 Intangible Assets and Rents

As explained by [14] Crouzet et al (2022), intangible assets are likely to generate rents for owner firms; earlier in the Introduction I mentioned that intangibles are usually firm-specific, and this degree of specificity also affects the degree of non-rivalry within the firm and across competitors. In those situations where intangible assets are characterized by a high degree of within adopter firm non-rivalry (meaning that the asset can be replicated at almost zero marginal cost) and at the same time cannot be appropriated by outsiders, it is possible that intangibles alter the competitive structure of those markets, by giving their users the power to raise prices for those goods that have no substitutes. For example, a pharmaceutical formula generates rents for its owners only if form of intellectual property protection ensure that other competitors cannot appropriate it and replicate the exact same drug.
Another meaningful example of the impact of intangibles on market power is trademarks and, more generally, brands: [25] Kost et al. find evidence both at the micro and macro level that an increase in brand concentration is associated to increases of firm-level profit margins and aggregate markups. More generally, [15] De Loecker et al. (2021) build a framework to quantify the impact of both technological change and market structure on markups: they find that both ingredients are necessary to motivate the observed rise of markups and the decline of business dynamism in the US. Intangibles fit into this framework, as they lead to a higher fixed cost for those entrants who do not adopt them and at the same time increase productivity, profits and the market share of their users.

6.2 The Relationship between Intangible Intensity and Industry Markups

To study whether those industries that are more intangible intensive tend to display a higher markup, I adopt an empirical strategy analogous to the one used for the investment gap. In particular, I use the firm-level markup estimates obtained in Section 2 and average them at the industry level, in order to obtain a single-figure for the industry markup. The level of aggregation that I use corresponds to the first three digits ATECO-2002 classification.
If I look at the simple correlation between markups and my measure of intangible intensity, namely the industry average of the intangible share s^{ι}_{ijt}, I find a positive correlation between the two variables across industries an time, as shown in Figure 11. The Pearson correlation coefficient is 17.05%, significant at the 1% level.

In order to refine the analysis and control for industry-level time-invariant endogeneity and time-varying aggregate shocks, I regress industry-level markups on the industry-level intangible share, including industry and time fixed effects and a set of industry-level controls, such as the industry

VARIABLES	(1) log(Markup)	(2) log(Markup)	(3) log(Markup)	(4) log(Markup)
Intangible Share	0.843***	0.849***	1.151***	1.045**
	(0.198)	(0.200)	(0.397)	(0.420)
Industry FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	405	405	405	405
R-squared	0.141	0.146	0.915	0.917

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Regression of industry-level markups on the industry-level intangible share

average Value-added and Sales:

$$log(\mu_{jt}) = \alpha_j + \delta_t + \xi s^{\iota}_{jt} + \delta X_{jt} + \epsilon_{jt}. \tag{8}$$

I expect the coefficient associated with intangible intensity ξ to be positive and significantly different from zero, meaning that industries where the intangible share of total assets has grown more are also those where markups have been rising the most. The results are reported in Table 7: as expected, the coefficient of interest is always positive and significant. In the specification with industry and year FE the estimate for $\hat{\xi}$ is 1.045, implying that a one standard-deviation increase in intangible intensity is associated to a 9.5% increase in markups. As a robustness check, in the Appendix I repeat the same analysis using concentration as an alternative measure of market power. Table 8 instead repeats the same analysis within each industry, using the first two digits of the ATECO-2002 classification to generate within-industry fixed effects: this dis-aggregated analysis shows that there is a wide industry heterogeneity in the way markups are related to intangible capital. I find a positive and significant coefficient only in the Manufacturing sector, which accounts for the largest portion of Value added in the total economy.

6.2.1 Measurement Error Correction

Also for markups, I correct for measurement error which could be arising due to noisy estimates of the industry-average intangible share. I apply the same procedure as in Section 4.5.2, and use the ISTAT industry-level average software adoption share to instrument the variation in industry intangible intensity. As shown in Table 9, the results confirm my findings of a positive association between intangible growth and markups.

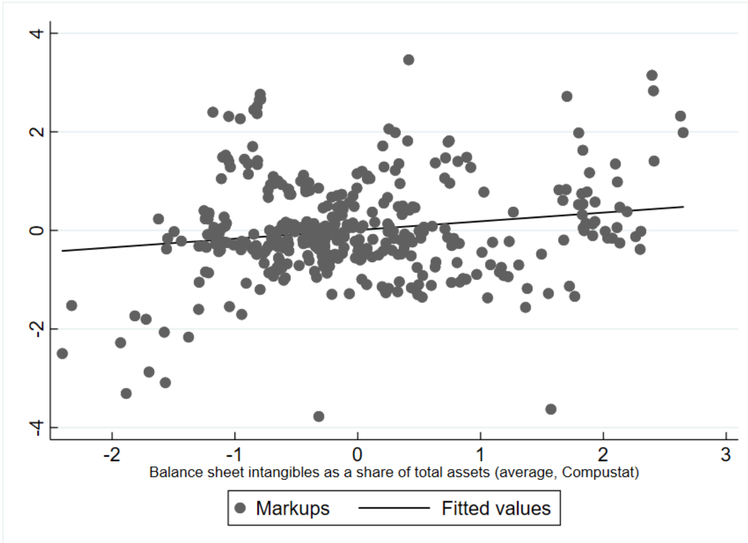

Figure 11: Industry-level correlation between average intangible share and industry Markups. For both variables, observation values are normalized with respect to the cross-sectional mean

VARIABLES	(1) Energy	(2) Manufacturing	(3) Services	(4) Transport comm.	(5) Wholesale Retail
Intangible Share	-1.566**	1.896***	-1.287***	1.161	-0.555
	(0.791)	(0.598)	(0.308)	(1.347)	(0.576)
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	54	198	36	27	54
R-squared	0.983	0.93	0.96	0.85	0.98

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Industry-variation in the correlation between intangible intensity and markups

VARIABLES	(1) $\log(\mu_{jt})$	(2) $\log(\mu_{jt})$	(3) $\log(\mu_{jt})$
Int.Share	-0.98**	2.55***	2.31***
	(0.92)	(0.82)	(0.59)
Instrument: average software adoption			
First stage F stat	26.41	14.58	27.56
Year FE	No	No	Yes
Industry FE	No	Yes	Yes
Observations	230	230	230

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Regression of industry-level markups on industry-level intangible intensity, instrumented by the average industry-level software adoption

7 Conclusion

Italian firms are rapidly shifting towards intangible-intensive production: my analysis confirms the rise of intangible capital for the Italian economy and considers some of its implications. First, I find evidence that an investment gap, defined as the mis-match between physical capital investment and valuation measures, exists also in the Italian economy: the gap appears to be widening and correlated, at the industry level, with measures of intangible intensity. Contrarily to the US case, documented among others by [21] Gutierrez and Philippon (2017) and [13] Crouzet and Eberly (2019) on sub-samples of listed firms, the Italian gap is wider when I look at the sample of both listed and unlisted firms. The gap closes when I look at total investment (in both tangible and intangible assets). This suggests that valuation measures based on Tobin's Q underestimate the role of intangible capital and hence place an upward bias on the contribution of physical investments to the measurement of Enterprise Value.

I also document the evolution of industry markups in Italy: these are generally flat, with a larger decline in the early 2000s. My evidence partially contradicts results from [16] De Loecker and Eeckhout (2020) and [13] Crouzet and Eberly (2019), who found an increasing trend in several measures of market power, including concentration and markups. The difference in results is likely to be driven by the fact that other studies run their markup estimation using samples of public firms only: this suggests that sample selection plays an important role in this type of exercise. I also find that markups are positively correlated with intangible intensity at the industry level. Both this correlation and the one with the investment gap are robust to different measures of intangible adoption and to different econometric specifications.

While existing work has focused on improving the measurement of intangibles and on documenting the existing correlation between intangible intensity, the investment gap, and several market power indicators, it is still difficult to make statement about causal links. To understand whether intangible capital is generating the observed changes that were the object of my analysis, it would be ideal to instrument the variation in intangible intensity. This could be done using policy changes that alter the relative cost of intangible investment, or any other event that shifts the incentive to invest in intangible capital without impacting directly on other forms of investment or on market structure.

Given the documented rise of intangible capital, future research will have to carefully consider its consequences from a policy perspective. In this respect, my findings have important implications: as mentioned in the Introduction, intangible capital is less collateralizable and ownership requires special contractual arrangements. As suggested by [13] Crouzet and Eberly (2019) and by [6] Blair et al. (2000), the scarcity of a proper market place for intangibles may have consequences for business lending, since intangible capital cannot be used as collateral as easily as tangible one. One possible implication is that business lending is more constrained in those industries that are more intangible-intensive. There, firms may have to rely relatively more on equity, diluting ownership and sometimes bearing a higher cost of financing. As an increasing portion of firms shifts to intangible investments, this could also have implications for monetary policy-transmission: as highlighted by [13] Crouzet and Eberly (2019), the rise in intangibles could weaken the effect of policies that use bank-lending as a main transmission channel.
Moreover, if there is a causal link that connects intangible adoption to market power, policies that are designed to enhance technology diffusion should be careful not to harm competition. In 2016, for example, the Italian government has launched the plan *Industria 4.0* with the aim to provide incentives for Italian firms to adopt digital technologies and other forms of innovative capital. Hence, understanding what are the implications of such technologies in terms of market power and investment dynamics is an issue of outmost importance.

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8 Appendix

8.1 Stylized model for Markup Measurement

Assuming that firm i at time t produces output Q according to the following production technology $Q_{it} = Q_{it}(x_{it}, K_{it})$ and that $Q_{it}(.)$ is continuous and differentiable with respect to its inputs, I can derive the following Lagrangian function related to the cost-minimization problem of the producer:

$$\Lambda(X_{it}, K_{it}, \lambda_{it}) = P_{it}^X X_{it} + r_{it}K_{it} + \lambda_{it}(Q_{it} - Q_{it}(X_{it}, K_{it}))$$

with P_{it}^X being the price of labor and r_{it} being the price of capital.
Hence, the first order condition with respect to labor will be:

$$\frac{\partial \Lambda(.)}{\partial X_{it}} = P_{it}^X - \lambda \frac{\partial Q_{it}(X_{it}, K_{it})}{\partial X_{it}} = 0$$

Since λ_{it} measures the marginal cost of production $\frac{\partial \Lambda(.)}{\partial Q_{it}}$, I can rearrange the terms of the previous expression and derive the following:

$$\left(\frac{\partial Q_{it}(X_{it}, K_{it})}{\partial X_{it}}\right) \frac{X_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^X X_{it}}{Q_{it}} \tag{9}$$

I will define the markup of firm i at time t, μ_{it} as the ratio of the Price of Output to marginal cost $\frac{P_{it}}{\lambda_{it}}$. In this way I can isolate λ_{it} using (5) and plug it into the markup formula, obtaining:

$$\mu_{it} = \alpha^X \frac{P_{it}Q_{it}}{P_{it}^X X_{it}} \tag{10}$$

8.2 Sector-level Descriptives

8.3 A model of Firm Value and Investment with Intangible Capital

I am going to summarize and describe a version of the model of firm investment developed by Crouzet and Eberly (2019), in order to show that: i) average physical Q overestimates the true incentive to invest in physical capital, generating significant bias in regressions of physical investment on Tobin's Q; ii) even regressions of total investment on total Q may remain biased.

Assume that the profit function for a firm disposing of two types of capital K_τ and K_ι has the following shape:

$$\Pi_t = A_t(\alpha K_{\tau,t}^\rho + (1-\alpha)K_{\iota,t}^\rho)^{\frac{1}{\rho}}$$

where $A_t$is a stochastic exogenous profit affecting the firm's profits, ρ is a parameter controlling

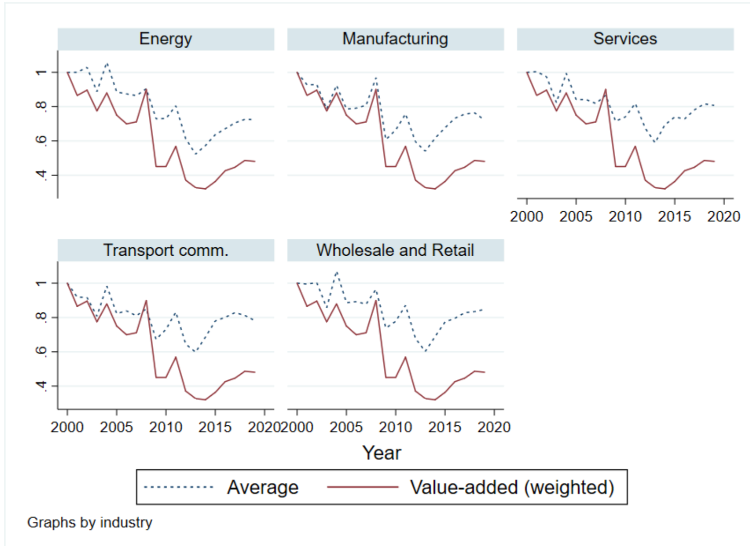

Figure A1: The figure decomposes the aggregate trend of physical investment in the 5 largest sectors of the economy in terms of number of firms and Value Added. The trend is reported in levels. The year 2000 is taken as a baseline.

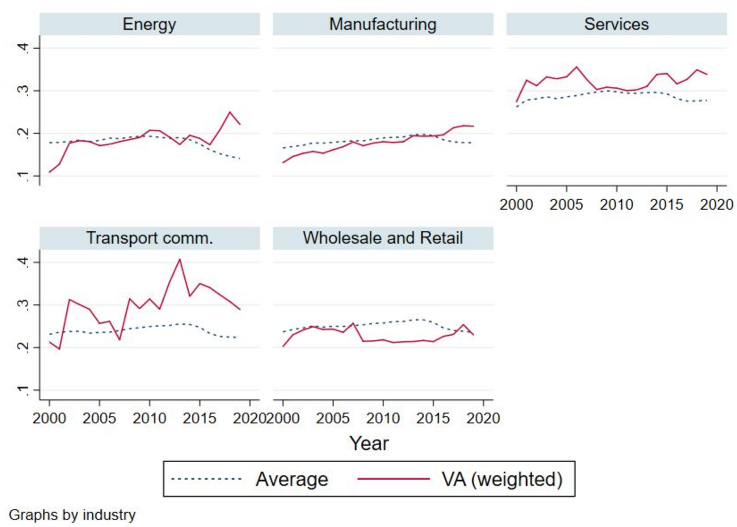

Figure A2: The figure decomposes the aggregate trend of intangible capital in the 5 largest sectors of the economy in terms of number of firms and Value Added. The trend is reported in levels.

the elasticity of substitution between the two capital inputs. Then, the firm is going to face the following value maximization problem:

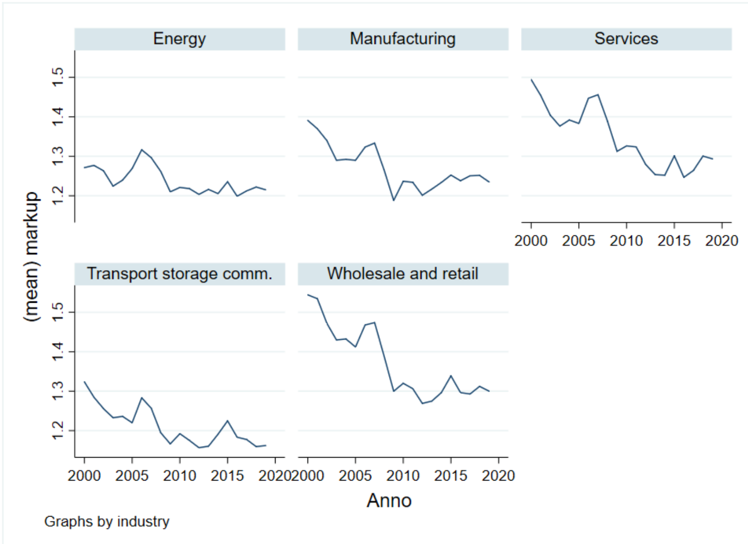

Figure A3: The figure shows the evolution of the mean markup, with each firm receiving a VA contribution weight for the 5 major sectors of the Italian economy in the last 20 years.

$$V(K_{\tau,t}, K_{\iota,t}; X_t) = max\, \Pi_t - C^{\tau}(K_{\tau,t}, I_{\tau,t}, P_{\tau,t}) - C^{\iota}(K_{\iota,t}, I_{\iota,t}, P_{\iota,t}) + \frac{1}{1+r} E_t[V(K_{\tau,t+1}, K_{\iota,t+1}; X_{t+1})] \tag{11}$$

subject to $K_{\tau,t+1} = I_{\tau,t+1} + (1-\delta_{\tau})K_{\tau,t}$ and $K_{\iota,t+1} = I_{\iota,t+1} + (1-\delta_{\iota})K_{\iota,t}$, with $X_t = (A_t, P_{\tau,t}, P_{\tau,t})$ being the collection of all the exogenous processes that enter the firm's problem. I also assume that investment for capital of type n has a cost function with quadratic adjustment cost of the following type:

$$C^n(K_{n,t}, I_{n,t}, P_{n,t}) = (P_{n,t}\frac{I_{n,t}}{K_{n,t}} + \frac{\gamma_n}{2}(\frac{I_{n,t}}{K_{n,t}})^2)K_{n,t}$$

where γ_n captures the curvature of the adjustment costs.

From equation (11) I can take the FOC with respect to investment and obtain the following expression determining the optimal investment function for capital of type n :

$$i_{n,t} = \frac{1}{\gamma_n}\left(\frac{1}{1+r}\underbrace{E\left[\frac{\partial V}{\partial K_{\tau}}(K_{\tau,t}K_{\iota,t}; X_t)\right]}_{q_{n,t}} - P_{n,t}\right) \tag{12}$$

Notice than that the value function can be decomposed as follows:

$$V(K_{\tau,t}, K_{\iota,t}; X_t) = q_\tau(\nu_t; X_t)K_{\tau,t} + q_\iota(\nu_t, X_t)K_{\iota,t}$$

I define the intangible intensity of the firm as the ratio of intangible to tangible capital $\nu_t = \frac{K_{\iota,t}}{K_{\iota,t}}$. Average physical Q is then defined as:

$$Q_{\tau,t} \equiv \frac{V(K_{\tau,t}, K_{\iota,t}; X_t)}{K_{\tau,t}} = q_\tau(_t; X_t) + \nu_t q_\iota(\nu_t; X_t) \tag{13}$$

Hence, I can isolate q_τ from (13) and plug it into (12) and get:

$$i_{\tau,t} = \frac{1}{\gamma_\tau}\left(\frac{1}{1+r}E[Q_{\tau,t}] - P_{\tau,t}\right) - \underbrace{\frac{1}{\gamma_\tau}\frac{1}{1+r}E[q_{\tau,t}]\nu_{t+1}}_{w_t} \tag{14}$$

Equation (14) shows that, as long as the firm is going to use both types of capital, average physical Q is going to systematically overestimate the incentive to invest in physical capital. The amount of the bias is measured by the term w_t, which is proportional to the firm-level ratio of intangible to tangible capital ν_t. This also mean that, when running regressions of the physical investment rate on valuation measures alike average Q, the coefficient associated with valuation will be biased. Assume now that, in order to correct for the bias elicited in the previous section, I define "total" Q as $Q_t^{tot} \equiv \frac{V(K_{\tau,t},K_{\iota,t};X_t)}{K_{\tau,t}+K_{\iota,t}} = \frac{1}{1+_t}q_{\tau,t} + \frac{\nu_t}{1+\nu_t}q_{\iota,t}$ and "total" investment as $i_t^{tot} = \frac{I_{\tau,t}+I_{\iota,t}}{K_{\tau,t}+K_{\iota,t}}$ which can be written as:

$$i_t^{tot} = \frac{1}{\gamma_\tau}\left(\frac{1}{1+r}\frac{1+\nu_{t+1}}{1+\nu_t}E_t(Q_{t+1}^{tot}) - \tilde{P}_t\right) + \left(\frac{1}{\gamma_2} - \frac{1}{\gamma_\tau}\right)\frac{\nu_t}{1+\nu_t}\left(\frac{1}{1+r}E_t[q_{\iota,t+1}] - P_{\iota,t}\right) - \frac{1}{\gamma_1}\frac{\nu_{t+1}-\nu_t}{1+\nu_t}\frac{1}{1+r}E_t[q_{\iota,t+1}]$$

where $\tilde{P}_t$ is the firm specific investment price, given by:

$$\tilde{P}_t = \frac{1}{1+\nu_t}P_{\tau,t} + \frac{1}{1+\nu_t}P_{\iota,t}$$

In this expression, the bias is generated by the fact that the *marginal* q of the two types of capital need not be equal, hence the last two terms in the expression above may not cancel out. Only in the case where $Q^{tot} = q_{1,t} = q_{2,t}$, then the investment- total Q regression would be correctly specified.

8.4 Investment Gap Estimates

Table A1 contains the regression estimates for corresponding to the investment gap shown in Figure 7.

8.5 The Investment Gap in the AIDA sample

Figure A4 reports the estimates of the investment gap in the aggregate and for the 5 largest sectors of the economy in the group of AIDA firms: in this case, there is no evidence of a gap between physical investment and valuation at the firm level. This is most probably due to the fact that listed firms in Italy are an extremely small sub-sample of the total economy, hence there is going to be a positive selection of those firms with the best performance, likely the firms who invest the most. Interestingly, when looking at the gap dis-aggregated at the industry level, it appears that it is negative only for the Service firms and for the Wholesale and Retail sector. Even if this result is not robust, it contributes to strengthen the hypothesis that the gap should be larger in those industries that rely more on forms of intangible capital.

8.6 The Relationship between Intangible Intensity and Concentration

In the following section I include the results of the industry-level regression of the Concentration index on intangible intensity: here, Concentration is defined as the VA-weighed HHI index for each industry.

My results are reported in Table A2: when I use concentration as a dependent variable, the coefficient estimates are positive and significant, with a larger magnitude than in the case of markups. In fact, according to the coefficient estimate from the specification in Table A.2, column (4), one standard-deviation increase in the intangible share is associated to a 4.5 average increase in industry concentration.

VARIABLES	(1) $i^{\tau}_{ijt}(CAPEX)$	(2) $i^{\tau}_{ijt}(CERVED)$
2013	-0.0306***	-0.0136***
	(0.000781)	(0.000657)
2014	-0.0229***	-0.0120***
	(0.000786)	(0.000685)
2015	-0.0155***	-0.00823***
	(0.000797)	(0.000711)
2016	-0.0225***	-0.00418***
	(0.000855)	(0.000730)
2017	-0.0213***	0.00112
	(0.000818)	(0.000787)
2018	-0.0316***	-0.0285***
	(0.000850)	(0.000755)
2019	-0.0532***	-0.0523***
	(0.000840)	(0.000766)
Q_{t-1}	0.000944***	-0.000575**
	(0.000326)	(0.000266)
$CashFlow_{t-1}$	0.0108***	0.00813***
	(7.48e-05)	(6.39e-05)
$ValueAdded_{t-1}$	-7.20e-06***	-3.21e-06***
	(5.43e-07)	(2.46e-07)
Constant	0.187***	0.191***
	(0.000908)	(0.000747)
Observations	1,982,851	2,184,298
R-squared	0.362	0.415

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1: the table reports the regression output from specification (1), first using as a dependent variable the physical investment rate defined as using physical CAPEX in the numerator, then using the CERVED own expenditure-based measure of investment

Figure A4: The investment gap in the AIDA sample

	(1)	(2)	(3)	(4)
VAR.	HHI	HHI	HHI	HHI
Int. Share	0.00499	0.00451	0.158***	0.160***
	(0.0379)	(0.0378)	(0.0428)	(0.0427)
Industry FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	312	312	312	312
R-squared	0.000	0.000	0.117	0.117

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: here I report the estimates from the regression of VA-weighted HHI on intangible intensity (industry level):

$$HHI_{jt} = \alpha_j + \delta_t + s^{\iota}_{jt} + \epsilon_{jt}$$