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THREE ESSAYS ON THE DETERMINANTS OF FIRMS' STRATEGIC DECISIONS

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Abstract

Every day, the firm's management must make critical strategic decisions that will determine the firm's success. The decision-making process of managers is impacted by various factors. My thesis aims to explain how market feedback from stock prices impacts company managers' decision-making processes through what is known as “learning from stock prices”. This process involves using information from the market prices, which aggregate data from a large number of various informed investors, to complement the managers' existing knowledge. Recent research has deepened into a new area of study, namely, the influence of peers' market prices on managers' decision-making processes. In the first paper, I explore how portfolio diversification affects the learning process from peers' stock prices and its impact on the firm's investment policy. In the second paper, I introduce a theoretical model that integrates the learning from peers' stock prices into the corporate payout decision-making process. The model provides case-specific managerial learning implications, which I test empirically on a panel of 629 US listed companies. Finally, I began investigating other factors that may affect firms' dividend payout policies and identified a potential research gap in examining the relationship between common ownership and payout policy. Thus, in the third paper I investigate how common ownership influences firms' payout policy decisions. The model is tested using a unique dataset that includes ownership information from 4,595 European listed firms with a diff-in-diff empirical approach.

Keywords: payout policy, investment policy, real decision makers, feedback effect, price efficiency, learning from peers' stock prices, managerial learning, product diversification, common ownership, institutional investors, corporate governance, family firms;

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Introduction to the thesis

When we refer to strategic corporate decisions, we mean all of the choices that firm managers make in order to maximize their firms' value.

These decisions might be related to achieving a specified capital structure, investing or not investing in an investment project, choosing the form of shareholder remuneration, entering a new market, or acquiring a new firm to diversify or expand the company's core business.

Although analyzing firm dynamics can be difficult, there has been a growing emphasis on the informativeness of secondary market prices and their influence on real decision-makers, particularly on firm managers, since the works of Hayek (1945) and Grossman (1976).

In fact, market prices are the outcome of an aggregation of information from multiple actors, both informed and uninformed, who operate in the markets.

Thus, they contain valuable information that can help firm managers complete their knowledge set.

It is often assumed that firm managers possess the most comprehensive knowledge about their companies and the sectors in which they operate, but this is not always true. In fact, we cannot rule out the possibility that outsiders¹ may have access to information that insiders lack, allowing them to make better and more informed decisions.

For instance, according to De Cesari and Huang-Meier (2015), foreign investors may have access to country-specific economic information that a multinational company operating in that country does not. Firms typically engage consultants to gather data that will assist them in making decisions. Overall, professional fund managers may outperform industrial firms in evaluating publicly available data and providing relevant private information.

Research in this field has expanded significantly in recent years, with many contributions concentrating primarily on investment policy, M&A, and capital structure decisions.

¹ such as speculators, informed traders, investment fund managers, etc.;

Following the approach of Bond et al. (2012), in the first chapter, "The real effects of secondary financial markets: an update survey of literature," I attempt to summarize the numerous strands toward which the research has evolved in order to identify the gap to work on.

One particularly interesting and novel stream of literature, is highlighted by the work of Foucault and Fresard (2014).

The authors developed a theoretical model demonstrating that managers' investment decisions are influenced not just by the price of their own firms, but also by the price of their peers' stocks, introducing the concept of "learning from peers' stock price".

Following their theoretical framework, the first paper (Chapter 2) titled "The effects of product diversification on managerial learning from peers' stock prices", investigates whether and to what extent product diversification within competing firms' product portfolios can mitigate the informational power of stock prices available to peers.

In my research, I utilized a new dataset that paired firms based on their product portfolio similarity coefficients, as determined by Hoberg and Phillips (2016). The results showed that when compared to less similar peers, a one standard-deviation increase in the valuation of peers with more similar product portfolios led to a 0.24 percentage point increase in investment ratio, which in real economic terms represents an annual increase of more than \$13 billion in total capex in my sample. Afterward, I focused on the firms' dividend payout policies.

Despite extensive research on this issue, only a few studies have focused on the relationship between stock prices and dividend payout policies. For example, De Cesari and Huang-Meier (2015) found that managers utilize stock prices to inform their dividend policy decisions but only considered their own stock prices, while excluding the impact of peers' stock prices. Adhikari and Agrawal (2018), on the other hand, discovered that industry peers' payout policies significantly affect a firm's dividend and share repurchase policies, but they did not consider the impact of market pricing on this relationship.

Therefore, in the second paper (Chapter 3) titled "Do market feedbacks affect corporate dividend policy?", I developed a novel theoretical model which has several implications. Firstly, when managers observe the market's feedback, the probability of

a company distributing dividends is lower than for a company whose manager does not learn from the market. Secondly, and uniquely in the managerial learning scenario, the covariance between the dividend policies of the two peers' companies increases with the stock price informativeness of its peers (π_B) and decreases with its own stock price informativeness (π_A). Thirdly, the covariance between the payout policies of two competing firms is larger in the managerial learning scenario than in the no-learning scenario.

To provide empirical evidence of these theoretical implications, I used as baseline specification a fixed effects model on a dataset of 629 US firms from 2002 to 2019. Finally, I began investigating various factors that may affect firms' dividend payout policies and identified a potential research gap in examining the relationship between common ownership and payout policy.

The phenomenon of common ownership arises when common investors acquire a stake in one or more firms in the same industry, and it has grown in strength over time with the proliferation of passive investment vehicles, such as ETFs.

Azar (2012) was the first to publish on the topic, establishing a positive relationship between markups and networks of common ownership. While several studies have concentrated on the anti-competitive impact of common ownership (with conflicting results), there has been little and recent literature on the influence of common ownership on corporate strategic decisions. Yet, no one has studied the impact of common ownership on firm payout policies².

Moreover, most of the existing literature has focused on the US context, neglecting the European context.

Therefore, in the third paper (Chapter 4) entitled "Common ownership and dividend payout policy in the European context", I used a novel and previously unexplored dataset³ that contains ownership information for 4595 European firms from 1998 to 2021, and computed profit weights for each of European firms at 3-Digit, 4-Digit, and

² In reality, Di Giuli et al. (2021) found that increasing common ownership leads to a stronger positive relationship between firms' dividend yield in a common owner's portfolio. They did not, however, take into account the overall impact of increasing common ownership on company payout policy decisions.

³ developed in collaboration with Federica De Ascentiis;

5-Digit NAICS level to investigate the impact of common ownership on corporate dividend policy empirically.

Using a multivariate fixed effects model and a Difference in difference approach to address the typical endogeneity concerns in ownership data, I demonstrated that an increase in the degree of common ownership led to a greater shareholder remuneration in terms of payout policy (i.e., the sum of cash dividend distribution and share repurchases). Interestingly, I found this effect is driven by an increase in the firms' share repurchase program rather than a cash dividend distribution.

Moreover, I discovered that the relationship is still positive and statistically significant in family-owned firms, particularly in those where the CEO and Chairman of the Board of Directors do not overlap, and is even stronger when institutional investors' ownership is higher.

The remainder of the work is organized as follows. Chapter 1 revisits the literature on the real effects of secondary financial markets. Chapter 2 presents the paper titled “*The effects of product diversification on the managerial learning from peers' stock prices*”. Chapter 3 presents the paper titled “*Do market feedbacks affect corporate dividend policy?*”. Chapter 4 presents the paper titled “*Common ownership and dividend payout policy in European context*”.

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Chapter 1: The real effects of secondary financial markets: an updated survey of literature

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Abstract

The purpose of this study is to provide a comprehensive review of the various strands of literature that explore the real effects of secondary financial markets and how they influence real decision-makers. By aggregating information from a broad range of investors in the financial markets, stock prices enable real decision-makers to infer knowledge relevant to making their real decisions. I have categorized the literature on this subject into two main strands: the impact of market prices on regulators, policymakers, and credit-rating agencies, and the impact of stock prices on corporate decision-making by managers. Through this process, I attempted to synthesize and reorganize the most relevant significant findings.

Keywords: real decision makers, learning from stock prices, corporate investment, corporate decisions, price efficiency, feedback effect.

1. Introduction

One of the main topics in finance is about the real effects of the financial markets. When we talk about the real effects of the financial markets, we refer to the following question: Do have financial markets an effect on the real economy? Answering this question is a challenging undertaking that has always been of significant importance within the literature. This is because by showing that financial markets influence the real activities of the economy it is possible to understand how they produce and aggregate information from a large number of traders and what are the inefficiencies which have led to the rise of the global crises of the last 20 years.

The literature surrounding this topic has branched out into various areas, including finance, macroeconomics, market microstructure, and asset pricing. This work aims to try to summarize the different research areas that have emerged over time and to provide an indication of the direction that future literature may take.

To begin, we must distinguish the effects of primary and secondary financial markets.

Even though it is in the primary markets that shares and debt securities are issued for the first time and the price formation process takes place, it is in the secondary markets that numerous traders exchange shares with each other determining their demand and supply and driving them toward their intrinsic value.

This work will mainly focus on the literature regarding the real effects of secondary financial markets.

However, in order to provide a comprehensive overview of the research in this area, a brief review of the literature on the real effects of primary financial markets will be presented.

An important line of research in this strand of literature studies how adverse selection or moral hazard problems affect primary financial markets, thereby limiting the ability of entrepreneurs and firms to raise external capital. Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) are among the researchers who have studied this topic. Gertler and Kiyotaki (2010) also explore this issue, introducing an agency problem between borrowers and lenders to endogenize market frictions. They find that restricting an intermediary's ability to obtain funds from depositors also hinders its ability to obtain funds from other financial institutions. Moreover, given that nonfinancial firms can obtain funds only from a limited set of financial intermediaries, disruptions of inter-bank markets can lead to crises that affect real economic activity. Two recent studies that explore the same topic are those of Gilchrist and Zakrajsek (2012), and Arellano et al. (2019). In the former, the authors re-examine the evidence on the relationship between corporate bond credit spreads and economic activity and found that shocks to the excess bond premium which are orthogonal to the current state of the economy, the Treasury term structure, and stock market returns cause economically and statistically significant declines in consumption, investment, and output as well as in equity prices, as a result of contraction in the supply of credit. In the latter study, the authors developed a model with idiosyncratic risk and financial frictions and demonstrated that a realistic increase in firm-level volatility can explain most of the decline in output and labor observed in the Great Recession. This is achieved through the tightening conditions in primary markets (an increase of firm

credit spreads and declining debt purchase), revealing how financial-market uncertainty interacts with the real sector of the economy¹.

Other papers follow different lines of research. For example, Almeida and Campello (2007) examined the impact of asset tangibility on a firm's ability to access external financing and how this affects investment decisions, particularly in situations where firms have limited access to credit. They found that assets' tangibility has no effect on the cash flow sensitivities of financially unconstrained firms but affects the credit status of the firm, thus firms with very tangible assets may become unconstrained. However, this positively affects the cash flow sensitivity of investment in financially constrained firms.

Brunnermeier and Pedersen (2009) investigated how the funding of traders can affect market liquidity and vice versa. They found that the funding of traders affects, and is affected by, market liquidity profoundly, given that when markets are illiquid, market liquidity is highly sensitive to further changes in funding conditions. That implies a large liquidity-driven divergence of prices fundamentals in different markets. Other recent studies also examined the impact of primary financial markets. For example, Doukas et al. (2011) analyzed the role of capital market conditions and adverse selection costs of equity on the financing decisions of the firm during hot-debt market periods. They showed how such periods can affect firms' capital structure. Pinto and Santos (2020), on the other hand, suggested how credit risk and flotation costs, and other factors affect the firms' choice between structured finance transactions and corporate financing operations.

About the real effects of secondary financial markets, the literature started approximately 70 years ago with Hayek's² paper: "We must look at the price system as such a mechanism for communicating information if we want to understand its real function" and also "It is more than a metaphor to describe the price system as a kind of machinery for registering change, or a system of telecommunications...". Hayek's work has served as a foundation for various strands of research that intersect finance,

¹ See also Keefe, 2014, that show a procyclical relationships between agency costs and IPO initial return, and He et al., 2017, that demonstrate the effects of shocks to equity capital ratio of financial intermediaries on cross-sectional differences in average returns for assets in different markets;

² "The use of knowledge in society" (1945);

macroeconomics, and asset pricing and these sentences synthesize the link among all the papers I cite in my review.

The main idea conveyed in these sentences is that the prices in secondary financial markets are not merely reflective of traders forecasts of future cash flows generated by the companies, but instead possess a significant informational value that affects the behavior of real decision makers (decision makers in the real side of the economy³), and in turn, impacts real economic activities⁴.

One way to organize this literature is to categorize it into four main strands based on the different impacts of prices in the secondary financial markets. These strands are: the effect of stock prices on the decisions of real-decision makers, on price efficiency, on the price formation process, and stock liquidity. These, in turn, are subdivided into different sub-strands. Each of these strands can be further subdivided into different sub-strands. However, it is important to note that these strands are not completely distinct from each other as many works address multiple aspects. Nonetheless, I aim to present this literature in a structured way that allows the reader to navigate it easily. The next four sections will delve into each of the four strands mentioned earlier, providing an overview of their development and breaking them down into their respective sub-strands. Section 2 discusses an overview of the effect of stock prices on the real decision of decision-makers. Section 3 discusses the effect of stock prices on regulators, policymakers, and credit-rating agencies. Section 4 illustrates the effect of stock prices on managers' corporate decisions. Section 5 summarizes the principal findings.

2. Overview of the effect of market prices on real decision-makers

“The primary role of the capital market is allocation of ownership of the economy’s capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation... and investors can choose among the securities that represent ownership of firms’ activities under the assumption that security prices at

³ See Bond et al. (2012);

⁴ Allen (1993) stated that optimal real decisions depend not only on internal information to the firm but also on external information, such as the state of the economy, the position of competitors, the demand by consumers, etc.;

any time “fully reflect” all available information”. The idea behind this popular sentence written by Fama in 1970⁵ is simple: the markets’ asset prices are the result of the aggregation process of the information held by the various agents operating into them. So, the final result is that by combining different pieces of information prices provide an accurate assessment of firm value allowing the agents to allocate their resources efficiently.

Many of the authors who published on these themes expressed the same idea. As I wrote above, also Hayek in 1945 expressed the same concept in his landmark work. The same belief is at the basis of Hellwig’s 1980 paper, in which the author stated that by aggregating information from different speculators, markets make single agents collectively more informed.

Baumol, in 1965, provided an advanced view of the phenomenon, stating that real decision-makers learn from the information contained in the market’s prices and use it to guide their decisions.

Following this reasoning, it is clear that prices do not play a passive role in the markets, rather, thanks to their information content, they can influence the choices of real decision-makers giving them a “feedback”.

This “feedback effect” is the key concept in the literature under review, as it implies that prices convey information as well as aggregate it.

In fact, if we assume that the markets are efficient, then the prices reflect all the information present on them and are able to guide real decisions efficiently. Conversely, if the markets suffer the effect of noise that reduces their efficiency, prices may not contain all the information available and consequently may create a bias in the decisions of the real decision-makers.

In this respect, Grossman in his work of 1976 stated that in the market there are both informed and uninformed traders. The former spend resources trying to obtain profitable information to form their expectations. The latter don’t spend resources to obtain information and form their expectations only by observing current prices being aware that prices reflect the information of informed traders.

⁵ “*Efficient capital markets: A review of theory and empirical work*”, Fama (1970). For an in-depth analysis of market models and of efficient resource allocation problems, see the book “*The theory of finance*”, Fama and Miller (1972);

Assuming that the market is made up of only one of the two classes of traders. In the first case, the information aggregation process would lead to efficient prices and would correctly guide the decisions of real decision-makers. In the second case, the prices determined by the market would not correctly reflect the information contained in it and would generate distortions to guide the decisions of real decision-makers. The effects on the real economy would be different.

Summarising, the main peculiarity of this line of research is to identify the effects that the transmission of information from markets' prices has on the decisions of the real decision-makers and how these decisions subsequently impact the real economy.

Starting from the works of the aforementioned authoritative authors, the literature has branched out into different strands about the impact that prices have on the different real decision-makers operating on the markets (managers, regulators, policymakers, arbitrageurs, investors, and speculators) and on their incentive to produce information and disclose it to the markets.

3. The effects of market prices on regulators, policymakers, and credit-rating agencies

Through the information's aggregation and transmission coming from a multitude of different investors, the financial markets provide many signals to regulators and policymakers, helping them to determine the actions to be taken to implement their policy⁶. For example, a central bank may use asset prices to infer information about inflation expectations or future demand shocks and adapt policy in response to Bernanke and Woodford (1997) or regulators might learn about bank health from bond prices and could use it for intervention decisions (Siemroth, 2019). The observation of the governments' behaviors during the last financial crisis highlights how they often use price movements to justify their actions.

Markets' prices, in fact, play an increasing role in the ongoing monitoring of financial institutions' risks. The markets' signals, mainly provided by asset prices, are incorporated into surveillance programs, and supplement supervisory and financial

⁶ Piazzesi (2005) documents that in the US, the Federal Reserve Bank is affected by market developments when setting monetary policy. See also, Feldman and Lavonian (2001);

information for purposes of corroborating supervisory risk determinations and evaluations. In this way, they become objective early warning instruments that improve the regulatory agencies' supervisory processes⁷.

According to this, Hart and Zingales (2011), criticizing the “too big to fail” idea, propose a capital requirement system for financial institutions based on CDS's market price. In fact, the price of CDS reflects the institution's solvency, since it signals the probability that it will be able to repay in full long-term debt. According to their model, when the CDS price rises above a critical threshold (demonstrating a lower degree of the institution's solvency) the financial institution can issue equity to bring it down. If this effort fails and the CDS's price stays above the threshold for a predetermined period, the regulator intervenes.

Moreover, since market prices are considered a useful source of information by the authorities, they also use the feedbacks provided by the markets to understand when their intervention is needed and to avoid that a financial crisis of a single financial institution can also spread through the interbank network to other financial institutions like happened in the 2007 crisis. Numerous papers into this strand of literature focused on the role of prices in the central bank's policy decisions.

Goldstein et al., (2011a), specifically, developed a model focusing on the effects that have, and have had, speculative attacks in currency markets on central bank exchange rate policies. The speculative attacks, containing a large amount of information from a large number of speculators, provide policymakers with an aggregate indication of the information held by them. The authors show that by observing the extent of such attacks, in fact, central banks, that is logical to think that are not fully informed about the fundamentals of the economy, may come to believe that fundamentals are bad and thus that it should abandon a determined regime.

Bond and Goldstein (2015) also, studied a model of information aggregation in financial markets, where information aggregated in prices is used by the government to make an intervention decision. They show that the use of market prices as an input for policy might create an endogeneity problem since governments rely on prices that

⁷ see Burton and Seale (2005);

are influenced by their own policies. In addition, this might reduce the stock prices' informativeness themselves⁸.

Baeriswyl et al. (2019) called this phenomenon “The Dilemma of Central Banks” by writing about the dual role of the central banks. On the one hand, the central banks observe and rely on markets' prices to better understand the fundamental state of the economy. On the other, with its policy, it influence the markets. So, a dilemma arises from this dual role. Using the methodology of coordination games under heterogeneous information they analyzed optimal monetary policy when the information accuracy of the central bank depends on its policy. Likewise, Siemroth (2019) analyzed under which conditions the financial market reveals policy-relevant information to the policymaker in a setting with noise and possible self-defeating prophecies.

Furthermore, in a recent paper, Siemroth (2021) developed a general model in which traders and policymakers interact in competitive financial markets deriving a necessary and sufficient condition to achieve an equilibrium in which traders reveal their information by trading, and policymakers use this information for policy purposes. He shows that under his assumptions the equilibrium reached has positive welfare consequences and leads to a Pareto-optimal outcome.

4. The effects of stock prices on managers' corporate decisions

Prices, like other decision-makers, impact the activities of firm managers. This happens not because managers lack adequate internal information to make strategic corporate decisions, but because the market fills in the gaps by sending the company feedback containing external information.

Also, Fung and Tsai (2015) talked about the “information hypothesis”, according to which managers may rely on the stock market as a source of information assisting them to make investment decisions.⁹

⁸ see also Boleslavsky et al. (2017);

⁹ The authors found two alternative channels through which stock markets affect corporate decisions: financing channel and agency channel;

Since the goal of this work is to provide a complete view of the literature developed in the various fields, perhaps the most efficient way to deal with this macro-strand is to divide it into the various micro-strands that compose it.

In fact, the market feedbacks affect managers' decisions on external investments, such as M&A transactions, or internal investments, such as whether to proceed with IPOs or cross-listings and on identifying the appropriate capital structure or dividend policy. Furthermore, several recent studies have demonstrated how stock prices impact corporate productivity and earnings forecasts¹⁰.

Finally, as a result of the enormous interest that some of these themes have aroused, the quantity of articles produced in some of these micro-strands has recently increased significantly.

4.1 The effects of stock prices on managers internal investment decisions

The relationship between market value and corporate investments began with James Tobin's 1969 paper, in which the author first tied investments to the parameter Tobin- q , which is the ratio of market capital valuation to the cost of acquiring new capital. Since then, several authors have written about the subject, resulting in a vast amount of literature.

Fama (1981) showed empirically that some macroeconomic variables (such as GDP) had a strong explanatory power for investment and that there is a positive relationship between current and lagged changes in stock market prices and investments. Furthermore, Barro (1990) demonstrated that lagged changes in real stock market prices have a great deal of explanatory power for the growth rate of investment by analyzing a US data sample from 1891 to 1921.

Because of these empirical findings, the researchers began to ask if managers followed the signals provided by stock market prices when making investment choices, even when such signals did not correspond to their own fundamental valuations.

¹⁰ About the first strand, see Bennet et al., (2020), which realized a Difference-in-Difference analyses based on exogenous shocks to stock price informativeness to demonstrate that an increase in the informativeness of a firm's stock price (through CEO's turnover decisions channel) causes an increase in the firm's productivity. About the second one, see Zuo (2016), which found that managers rely more strongly on stock returns in revising their earnings forecasts when the amount of investor information in stock prices is higher since they learn from private information in prices about their own firms' fundamentals when making earnings forecasts;

However, the first results didn't confirm this idea. Indeed, Morck et al. (1990) found in their firm-level regressions that when fundamentals are held constant, changes in relative share prices are linked with large and statistically significant investment changes. Nevertheless, the authors asserted that this association exists not because markets provide more information to managers about the prospects of their own firms, but rather because markets apply some sort of pressure on managers who guide their decisions.

Using a different approach¹¹, Blanchard et al., (1993) achieved the same results. They concluded that, while theory gives conflicting signals about the effect of market prices on managers' decisions, empirical evidence suggests that, given fundamentals, market valuation appears to play only a minor role in influencing investment decisions.

On the other hand, the most recent literature shows that changes in the stock price have a very strong influence on managers' behavior.

Specifically, the feedback effect can influence managers through two channels: the first one is the stock price of the company headed by the manager ("learning from their own stock price"), and the second one is the stock price of its competitors ("learning from peers' stock price").

The influence is determined in the first channel when stock prices deviate from their fundamental values (the effects of mispricing on managers' investment decisions) or when unknown to managers external information is incorporated into the price (the effects of external information on managers' investment decisions). Instead, in the second channel, the manager observes the trend of his closest peers' stock prices before determining its corporate investment policy because they provide the manager with additional information on the prospective dynamics of the sector to which they belong, or, more broadly, the state of the economy.¹²

¹¹ Morck et al., (1990) used a panel data approach. Conversely, Blanchard et al., (1993) used a time series approach;

¹² if you think of a multinational firm's manager. According to De Cesari and Huang-Meier (2015), foreign investors which trade stocks of the firm in a country different to that of its headquarter, may have greater information about the state of the economy of that country compared to firm's manager;

4.2 The effects of mispricing on managers' investment decisions

About the first line, referring to "the effects of mispricing on managers' investment decisions", the logic is the following: when stock prices move away from their fundamental values due to exogenous factors, provide biased informative feedback to managers that could affect their investment choices. In that respect, Stein (1996) identified two channels through which mispricing affects investments: market timing and catering. According to the market-timing effect, managers exploit mispricing by issuing overvalued stocks to profit from a low cost of equity and postpone issuing underpriced equity to avoid a high cost of equity. The catering effect means that managers cater to the firm's short-term shareholders, focusing on the present stock price rather than the firm's long-run worth. His model suggested that enterprises that most need to use the equity financing channel are more sensitive to the nonfundamental component of investment stock prices. Thus demonstrating the existence of a distinct channel (equity financing channel) via which stock prices affect managers' investment decisions. Stein departs from earlier interpretations found in the literature¹³. Baker et al., (2003) and Campello and Graham (2013) also confirmed the existence of this channel testing their model several implications of the financing channel.

Specifically, Campello and Graham (2013) assessed the impact of the 1990's tech bubble to understand how the rise in equity valuation influenced companies' investment policies. Their empirical analysis revealed that, whereas the nonfundamental component of prices had no influence on the investment of financially unconstrained manufacturers during the tech boom, mispricing had a positive and large impact on the investment of constrained manufacturing firms.

Furthermore, they proved that the channel through which this effect manifested is that of equity financing: in fact, they discovered that financially constrained firms in non-

¹³ In contrast with Morck et al., (1990) and Blanchard et al., (1993). See also Galeotti and Schiantarelli, (1994), that find explanatory power in the irrational component of stock prices, Chirinko and Schaller, (1996) and Lamont (2000);

bubble sectors issued more shares in response to mispricing during the tech bubble's period and used the proceeds to increase investments rather than cash holdings¹⁴.

Alzahrani and Rao (2014) discovered that total investments are impacted by market-timing motivated equity issuance using Stein's framework and verified the concept that highly financially constrained firms demonstrate increased sensitivity between investment and stock mispricing. Furthermore, they showed that the sensitivity to investment mispricing is substantially larger in firms with short-horizon shareholders than in firms with long-horizon shareholders (confirming the catering channel).

Recent studies examined the consequences of mispricing on managers' investment decisions from distinct viewpoints. Concerning high stock price levels, Chan et al. (2017) found that corporate investment sensitivity to the stock price is lower for firms with higher stock price levels because it impedes informed trading on the stocks, limiting price informativeness. Their data revealed that managers of higher-priced firms concentrate less attention on stock prices when making investment choices. When firms require less feedback from stock prices, they maintain their stock prices higher, allowing them to avoid the undesirable repercussions of lower stock price levels.

On the contrary, if managers require more market information, they will seek to lower price levels through stock split operations, allowing them to rely more on stock prices. Dessaint et al. (2019), on the other hand, concentrated on the effects of nonfundamental shocks on stock prices. They show that nonfundamental shocks¹⁵ have an impact on corporate investment because managers have a limited capacity to distinguish information from noise when interpreting stock prices as signals about their prospects. They found that the more sensitive a firm's investment is to noise in its peers' stock prices, the fewer managers can filter out this noise from pricing and the more he depends on peers' stock prices as an extra source of information.

Using a novel approach based on managers' observations of peers' stock prices and mutual funds' fire sales as an instrument to analyze the effect of nonfundamental

¹⁴ Panageas (2005b), also, studied how managers react to deviations from their fundamental value of stock prices during speculative attacks. Analysing a scenario in which there is a strong limitation to short selling, which generates a deviation of market prices compared to their fundamental values, the author concludes that investments react positively with respect to these price deviations.

¹⁵ they argued that stock prices respond to both fundamental shocks (news) and nonfundamental shocks (noise);

shocks to stock prices, the authors showed that an average firm in their sample reduces its investment in fixed capital by 1.5% following a one standard deviation decrease in the nonfundamental component of its peers' stock prices, with the resulting loss in aggregate investment estimated to be about \$29 million per year¹⁶.

To conclude, Dong et al., (2020) tested how stock price overvaluation affects corporate innovation. Overvaluation allows the firm to relax financing constraints while maintaining a high stock price. They investigated whether misvaluation predicts innovative input (R&D expenditures) and innovative output (patents and patent citations). Their strategy helps them to overcome the price endogeneity issue in terms of potential for innovative investments. Their major finding is that overvaluation is strongly associated with increased intangible investments and resulting outcomes (R&D, patents, and patent citations). Furthermore, the sensitivity of research and development to misvaluation is larger than that of capital expenditures to misvaluation¹⁷.

Finally, in contrast to most of the existing literature, Bakke and Whited (2010) discovered that firms with high levels of mispricing and big enterprises consider mispricing irrelevant for investment decisions using an econometrics errors-in-variables methodology. Furthermore, they discovered only a minimal indication that financially constrained companies consider market mispricing when making investment decisions.

4.3 The effects of external information on managers' investment decision

The second line relates to "the effects of external information on managers' investment decision". This literature comprises all works that investigate how external corporate information (such as the status of the economy), its amount, and its production affect market pricing and managers' decisions regarding the firms' investment policy. On a conceptual level, this line of research intersects with the "Price Efficiency" literature strand, which began with the 1980 publication by Grossman and Stiglitz. The "Price

¹⁶ to deepen the literature on the effects of noisy stock prices see Stein (1996), Polk and Sapienza (2009), Edmans et al., (2012), Hau and Lai (2013), Williams and Xiao (2017), Luo and Wang (2018), Xiao (2020), Wardlaw (2020), Jiang et al. (2021) Jajaraman and Wu (2021);

¹⁷ Polk and Sapienza (2009) stated that the effects of misvaluation on innovation activity and inventiveness are especially important among firms with higher catering incentives;

Efficiency" strand, on the other hand, is primarily concerned with the study of markets' efficiency in transmitting trader information in prices and, as a result, their informativeness.

On the other hand, the "External information" strand focuses on how the information presented in markets' prices influences the investment decisions of managers and their efficiency. Regarding the investments' efficiency, Durnev et al., (2004) showed that the level of Tobin's marginal q ratio¹⁸ of companies belonging to the industries whose stocks exhibit greater firm-specific return variation (i.e., in which stock prices are more informative) is not very far from their theoretical optimum level (i.e., 1), demonstrating greater efficiency in their investment policy. Bade and Hirt (2016) explored a model that connects the effects of endogenous private information acquisition and the decision makers' mechanism of learning from prices, demonstrating that endogenous private information acquisition results in a tradeoff between investment efficiency and liquidity cost. Dow et al., (2017) concluded that the production of information in financial markets has a positive effect on firm value since it leads to more efficient investment decisions¹⁹.

The more recent papers deal with this theme is that of Xu (2021) and Vo (2021). They used two different approaches. Xu (2021) empirically investigated whether stock price informativeness affects managerial inefficiency in making corporate decisions finding a negative relationship between the Probability of Informed Trading (PIN), which proxies the informativeness of the stock prices, and firm value shortfalls, which captures the degree of managerial inefficiency. The author found that stock price informativeness reduces managerial inefficiency through the mechanisms of learning hypothesis²⁰.

¹⁸ it is the change in firm value due to unexpected changes in investment scaled by the expected change in investment. To assess the efficiency of corporate investments, the authors considered as a measure of investment efficiency the deviation in Tobin's marginal q from its optimal level: the smaller the deviation the greater the investment efficiency;

¹⁹ Moreover, they found that speculators tend to produce more information in times in which economy is good than in which it is bad generating an amplification mechanism which leads to large drops in investment activities and firm valuations in response of small deterioration of fundamentals;

²⁰ Pedraza (2019) provides a different view of the learning mechanism: the author modelling a strategic game between firms and informed speculators showed that the learning process contains an endogenous component. In particular, he found that learning from prices' channel is limited because prices are endogenously less informative for firms with low quality of managerial information (i.e., the prices

Vo (2021), on the contrary, developed a theoretical model to study the role of the capital structure policy on the informational efficiency of stock prices. He found that managers can control the capital structure of their firm and can affect the informational efficiency of their stock prices only when the firm has incomplete information and needed of feedback from the market to bring efficient operating decisions. Otherwise, the Modigliani-Miller irrelevance is maintained.

Other papers focused on the influence that macroeconomic factors have on investment-to-price sensitivity. Durnev (2010) identified a "political channel": he proved that the uncertainty surrounding political elections affects the sensitivity of investments to stock prices and company performance in the months immediately following them. This effect might be generated by two factors: the first is a decrease in the informativity of the share price as a result of any policy change that discourages trading activity during such periods²¹; the second concerns the degree of political connection that each company possesses.

Indeed, the author found that if managers with political affiliations had access to privileged information or government financing, investments will be less responsive to stock prices.

Furthermore, he discovered that the decline in investment-to-price sensitivity is more evident in nations with significant corruption, big state ownership, and a lack of transparency about politicians' business and financial interests. Farooq and Ahmed (2018), on the other hand, are concerned with the influence of inflation on the link between investment and stock prices²².

They discovered that higher inflation diminishes pricing efficiency, resulting in less dependence on stock prices by managers and lesser sensitivity of investment to stock prices. This effect is less pronounced in nations with better governance and an information environment.

informativeness of companies whose managers have low quality prior information, that is, who need more to learn from prices, is lower and vice versa);

²¹ This effect is the greater the more the degree of uncertainty of the election;

²² For more information about the literature on the effect of inflation on investment-to-stock prices sensitivity see also Friedman (1977), Modigliani and Cohn (1979), Tommasi (1996), and Ball and Romer (2003);

Furthermore, Chen et al. (2020) concentrated on the influence of financial market openness and information from foreign investors on investment-to-stock price sensitivity. The findings show that opening financial markets to global investors enhances the investment efficiency of the firms that comprise them by focusing on developing markets. Furthermore, a rise in information, mostly about the product market and the technological frontier, leads to an increase in the learning process by managers.

The firm's disclosure is another source of external information impacting corporate managers' decision-making decisions.

In reality, when a company decides to publish internal information, it is because it wants the markets to provide feedback on the additional information that has been provided to them. In this way, the manager increases the information content of her firm's stock price.

Ramanan (2015) applies this concept to disclosure regarding new product initiatives. According to the author, in order to maximize the informative content of market feedback, the firm should separate the disclosure about the new product initiative from the issuance of the earnings report, because otherwise, the firm would receive combined feedback from the market, which would not allow managers to understand whether the markets are for or against the launch of the new product.

If the firm releases the two pieces of information separately, the management may get a clearer understanding of how investors evaluate the new product by observing the change in the price of corporate shares. This also explains why companies are often reluctant to reveal or discuss new financial information during key information events such as product launches or M&A announcements.

Following this line, Arya et al. (2017) showed that disclosure of financial reporting minimizes market-level uncertainty and provides unambiguous feedback from the market about current ventures and the efficacy of the company's new technology. Making these reports public, however, has a dual effect: on the one hand, as previously stated, it reduces market uncertainty by minimizing the informational gap between liquidity investors and speculators; on the other hand, it reduces speculators' incentive

to produce information on the company by weakening the informational content of the stock price²³.

This concept is also taken up by Gao and Liang (2013) who identified the process of a company's confidential data disclosure as "expensive" as it reduces the informational feedback from the stock price. When the firm looks to the stock price for guidance, the more it has disclosed, the less news it gleans from the stock price. It implies that the investment decisions that rely on the information in the stock price become less efficient.²⁴

Finally, the last part of this strand focuses on the role of the information production of external information.

A milestone on this issue is the paper written by Chen et al., (2007). They argued the information that managers seek to learn by observing market prices is primarily about the product demand or the market strategy of their competitors. Their empirical model showed that managers who possess more prior information rely less on the market prices when bringing their investment decisions.

Furthermore, they found the stocks that provide more information to managers are those that possess a large amount of private information²⁵.

Following the same logic, Fresard (2012) empirically found that stock prices with large content of private information affect managers' decisions about cash savings. Da Silva (2021), rather, provides an empirical confirmation of the results found by Chen et al., (2007) and widens the sample of firms using a dataset composed of data about firms from all over the world. Furthermore, he stated that only price efficiency indicators capturing the amount of private information incorporated in stock prices influence the investment-to-stock price sensitivity.

²³ Also Bade (2017) showed that the disclosure of firm's internal information that follows the announcement of an M&A deals reduce the speculators' informational advantages and motivates them to produce less precise private information reducing the price informativeness. This effect contrasts with the incentive to produce private information that speculators have before the news concerning M&A;

²⁴ They also showed that this effect is greater for growth firms, as they rely more on stock prices as a source of information. They will make less disclosure to attract more private information production useful for providing to managers business decisions' feedbacks from the markets;

²⁵ This does not imply that this stock prices are close to their fundamental values, as these will depend on the overall degree of information present in the securities and not only on private information;

Edmans et al., (2017) building a theoretical model based on the effects of an Insider Trading Enforcement (ITE) on the total amount of information in prices²⁶ showed that such enforcement, by rising the RPE, significantly increases the sensitivity of investment-to-q.

Lastly, Bernard et al. (2020) investigated the links between firm information acquisition and corporate investment, developing a direct measure of these information flows at the firm-pair level. They concluded that managers examine their rivals' R&D expenditure and use that data to determine the amount of investment required to remain competitive in the market. The empirical results show a greater product differentiation between the company that observes and the company from which the information comes, proving that companies competing in the same market have strong incentives to differentiate their products in order to gain market share and pricing power.

4.4 Learning from peers' stock price

The third line refers to “learning from peers’ stock price”. In fact, until now we have always treated models (theoretical and empirical) based on the informational role that the firm’s own stock price has for the company’s manager.

However, if we believe that managers utilize all types of information to minimize their information gap and maximize the value of their firms, then the price of their own shares, as well as the price of their competitors' shares, will provide them access to the same crucial market feedback.

This view is even more logical if we consider the frictions present in the markets that can generate distortions in stock prices. Therefore, the managers of the company will look favorably at the prices of their competitors, especially to analyze the trend and the risks of their own industries.

Foucault and Fresard (2012) are the first to talk about the "Learning Mechanism" by addressing, however, the learning mechanism of information from the prices of their stock prices by managers who hold shares listed on various exchanges (cross-listed companies).

²⁶ They distinguish the “forecasting price efficiency”, as the indicator of the total amount of information in prices, from the “revelatory price efficiency”, as the indicator of the amount of information in prices not already known to the decision maker. See also Bond et al (2012);

This concept was taken up and expanded by Ozoguz and Rebello (2013) who, on the other hand, were the first to develop the concept of "Learning from peers' stock price". The authors found that the IO of the firm and its industry, the strategic threat posed by peers, and the information mix in peers' prices are strategic factors for the investment response to the change in peers' stock prices²⁷.

Specifically, they showed that an increase in the average of peer firms' stock prices is associated with a statistically significant increase in the firm's capital expenditure. However, the first paper to build a theoretical model that determined that peers' stock price is influential in the managers' investment decisions is that of Foucault and Fresard (2014).

The two authors developed a model in which peers' valuation complements managers' knowledge about their investment opportunities to test the hypothesis that peers' stock price valuation and their changes affect the investment policy of the firm by completing the information available to the managers about the firm's growth opportunities.

They showed that exists a positive relationship between a firm's investment and its peers' valuation and that this sensitivity of the firm's investment to its peers' stock price decreases with the quality of managers' private information and with the informativeness of the firm's stock price.

In fact, if the managers own high-quality private information or if the informativeness of the firm's own stock price increases, they put less weight on the peers' stock price to evaluate their growth opportunities, reducing the sensitivity of the firm's investments to its peers' stock price.

Huang e Zeng (2015), analyzing investments cycles across different industries found that cross-learning may lead to higher investment inefficiency generating a spiral behavior of the managers that leads companies, especially those belonging to the same industries, to put higher weight on the information about the common shock amplifying its effects²⁸.

²⁷ In fact, they demonstrated that, for more competitive industries, the sensitivity of investment to Peer Q decreases substantially and that the sensitivity of investment to Peer Q changes with measures of price informativeness in ways that are consistent with the information mix captured by each measure;

²⁸ They stated that cross-learning (within a single industry) first makes different firms' investments more correlated with the common shock they suffer increasing speculators' trade on stocks. Then, assets

However, it is reasonable to believe that managers' mimicking behavior can only be true in markets that are extremely rich in information, such as those in the United States. In this context, Mama (2017) emphasizes how this behavior is improper for European markets.

Indeed, a fundamental distinction between the European and American markets is the European market's country-level high fragmentation of market infrastructures in comparison to the American market. This reduces the overall information on the stock prices of specific firms.

Furthermore, there is contradictory evidence to consider: on the one hand, European managers adopt more conservative strategies than their US-based equivalents; on the other hand, Mama finds stronger evidence that managers in continental Europe have better internal information than their counterparts in the UK and the US. This leads to the finding that European managers learn less from stock prices. Moreover, they do not show to change away from basing their value on their stock prices, even as peer stock prices become significantly more informative.

More recent works introduce a new literary strand. Dessaint et al., (2019), as already written above²⁹, analyzed the effect caused by non-fundamental changes in the peers' stock prices³⁰ on the investment decisions of managers whose observe these prices in the market and through the "learning mechanism" use the information within their investment decision-making process. They specifically noted that because managers have little ability to distinguish between fundamental and non-fundamental shocks (noise in stock prices), peers' stock prices may send a "faulty informant" signal to managers, distorting their investment policy.

Yan (2020) focused, on the other hand, on the role that the "learning channel" has in affecting the investment policy of private firms' managers. The basic idea is that private company managers, by studying the stock prices of their listed counterparts, improve their information and apply it to their investment policy.

become more informative taking firms' managers to rely more on them. Finally, firms' investment sensitivity to the common shock increases even more by boosting the initial effect and by leading firms to invest more;

²⁹ See the section "The effects of mispricing on managers' investment decisions";

³⁰ They used stocks' sales by mutual funds due to investors' redemptions which entail large negative nonfundamental demand shocks and a downward price pressure;

Based on a dataset of UK firms, she finds that private firm investment responds positively to industry valuation, as proxied by the average beginning-of-period market-to-book ratio of all public firms in the same industry, implying that the market influences not only the efficiency of the investment choices of listed company managers but also of private ones.

Furthermore, in line with Dessaint et al. (2019), she shows how the inability of private firm managers to filter out the noise component from stock prices in the same way as their public company counterparts cause them to be affected by non-fundamental changes (noise) in their peers' stock prices³¹.

To conclude, Lee (2020) examined a different channel through which the learning from peers' stock price can influence managers' investment decisions. In fact, he hypothesized and found that there is a positive relationship between the target shareholder gains and peer firm returns after an M&A deal. The ultimate result is intriguing: investors, given the new information revealed by the deal announcement, alter the values of competing companies whose mergers and acquisitions have occurred³². It would be interesting to understand if and how this affects, through the “learning from peers’ stock price” mechanism, the investment decisions of the managers of the companies operating in the same industry.

The core idea is that M&A transaction announcements considerably improve the information available to evaluate the future of the sector in question, impacting managers' investment policy decisions at firms in the same industry through changes in peer stock prices.

Using the same approach, it would be interesting to investigate how the findings of Hope and Zhao (2018) might produce a learning effect within an industry, affecting the stock prices of its constituent firms and, as a result, their investment decisions. In fact, the two authors found that if the market thinks that the peer company's analyst revisions contain new material information about the peers company, investors would update their estimate of the peers' stock prices.

³¹ In fact, she empirically finds that private firms’ investments reacts positively and significantly to the noises in their peers’ stock price;

³² That is, investors may expect similar deal premiums from potential takeover offers with regard to companies belonging to the same industry;

Understanding the scope of these effects within the same industry might be an intriguing area to begin the study.

5. Main findings

Over the past 30 years, the literature on the real effects of secondary financial markets has developed and impacted various academic fields. In this review, I aimed to highlight the key themes and ideas in the literature and found that one of the most interesting and expanding topics is related to firm managers learning from peers' stock prices.

Despite the impact of secondary markets on many real decision-makers, this line of research investigates how stock prices, which aggregate information from various informed traders, affect strategic business decisions made by firm management. One open research question that my future work will address is the influence of portfolio diversification on this mechanism and its impact on dividend payout policy.

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Chapter 2: The effects of product diversification on the managerial learning from peers' stock prices

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Abstract

The purpose of this study is to investigate whether diversification of product portfolios among competing firms leads to greater learning by management from the stock prices of their peers. To accomplish this, I built upon the theoretical model developed by Foucault and Fresard (2014) by adding a variable that takes into account the level of product portfolio diversification among the two competing firms. My findings indicate that an increase of one standard deviation in the Tobin's Q of peers with similar product portfolios predicts a rise in the investment ratio by approximately 1.6 percentage points compared to the peers with less similar product portfolios. Additionally, this relationship becomes more prominent with decreasing scale factors, as there is a trade-off between product portfolio diversification, stock price informativeness, and covariance between a firm and its peers' stock prices. To the best of my knowledge, this study is the first to demonstrate that a higher level of product portfolio homogeneity raises the informativeness of the peers' stock price and fosters the company's manager's learning from peers' stock price mechanism.

Keywords: real decision makers, learning from peers' stock prices, corporate investment, corporate decisions, price efficiency, feedback effect, product diversification, managerial learning;

1. Introduction

A growing body of research on the relationship between financial markets and the real economy is focusing on the impact of secondary financial markets on the investment decisions made by firm managers¹.

This line of literature started with Hayek in 1945²: “we must look at the price system as such a mechanism for communicating information if we want to understand its real function”. The main idea behind these words is that secondary financial market prices are not passive indicators of expectations about future cash flows produced by companies, but they also have a high informative content that influences the actions of

¹ Subrahmanyam and Titman (1999), Graham and Harvey (2001), Baker et al. (2003), Chen et al. (2007), Foucault and Fresard (2014);

² “The use of knowledge in society” (1945), American Economic Review;

real decision makers (decision makers in the real side of the economy³), and thus they have an impact on real economic activities⁴.

Managers frequently rely on peers' stock prices to predict industry growth opportunities or the status of economics, given that they provide important information that complements that accessible from internal sources (e.g., the firm's own stock price, internal information, financial analysts' reports).

This phenomenon has been the focus of recent research, with Ozoguz and Rebello (2013) being the first to demonstrate the "learning from peers' stock prices" mechanism, showing that a rise in the average stock price of peer firms is associated with a statistically significant increase in a firm's capital expenditure. Foucault and Fresard (2014), subsequently developed a theoretical model that revealed a positive relationship between a firm's investment and the valuation of its peers.

They also found that the sensitivity of the firm's investment to its peers' stock price decreases with the quality of managers' private information and with the informativeness of the focal firm's stock price.

Huang and Xeng (2015) conducted research on investment cycles across industries and found that cross-learning could lead to increased investment inefficiency. This, in turn, could result in a spiral behavior among managers, especially those in the same industries, as they rely heavily on information about common shocks, amplifying their effects⁵.

Furthermore, Dessaint et al. (2019) investigated the impact of non-fundamental changes in peers' stock prices on the investment decisions of managers who observe the prices in the market and use the knowledge inside their investment decision-making process via the "learning mechanism". Meanwhile, Yan (2020) focused on the importance of the "learning channel" in influencing the investment policy of private firm managers.

³ See Bond et al. (2012);

⁴ Allen (1993) stated that optimal real decisions depend not only on internal information to the firm but also on external information, such as the state of the economy, the position of competitors, the demand by consumers, etc.;

⁵ They stated that cross-learning (within a single industry) first makes different firms' investments more correlated with the common shock they suffer increasing speculators' trade on stocks. Then, assets become more informative taking firms' managers to rely more on them. Finally, firms' investment sensitivity to the common shock increases even more by boosting the initial effect and by leading firms to invest more;

My research aims to determine if and to what extent product diversification within the corporate product portfolio can limit competitors' accessibility to stock price information.

The main idea is that managers can gain more information by observing changes in the stock prices of their peers with more similar product portfolio than by monitoring those of their peers with more diversified portfolios in the market. Thus, managers may utilize product diversification as a defensive mechanism against strategic imitation by their peers to maintain the company's competitive advantage.

o examine the relationship between financial information and the structure of competitors' product portfolios, I developed a theoretical model that links product portfolio homogeneity to the covariance between a company's investment policy and the stock prices of its peers.

The model, which extends Focault and Fresard's (2014) approach, is based on the intuition that increasing the homogeneity of goods in competitor firms' portfolios results in a stronger correlation between a firm's investment decisions and the competitor's stock prices. The model assumes that a firm sells a product with uncertain demand that is correlated with that of its competitor (its peer).

The degree of homogeneity of the demand shocks common to both firms and the degree of similarity of their products portfolio will determine the demand correlation between the two companies.

The firm's manager must decide whether to expand production capacity or not. This growth opportunity has a positive net present value only if future demand for its firm's product is strong enough.

While investors trade on private information about future demand, the firm's stock price and its peer's stock price provide signals to the manager about the net present value of the growth opportunity, in addition to his own private information.

To make the model more realistic, I suppose that informed traders who receive information concerning one of the two firms will use this information to invest in the other based on the degree of homogeneity in their product portfolio.

The underlying logic is that an informed trader who obtains private information about firm A will trade not just on firm A, but also on firm B (a competitor of firm A) in

proportion to the degree of similarity in the two companies' product portfolios⁶. To determine the level of product portfolio homogeneity between firms, I utilize Hoberg and Phillips' similarity coefficient⁷ based on firm pairwise similarity scores from text analysis of firm 10K product descriptions.

According to *Result 1* of my theoretical framework, I tested if managers' investment decisions are influenced by changes in the stock prices of their peers who have a more similar product portfolio.

Using a fixed-effects (within estimator) model as the baseline specification, I found that, all else being equal, a rise in one standard deviation of the Tobin's Q of peers with more similar product portfolios implies an average increase in capex ratio of roughly 0.24 percentage points when compared to the same change in less similar peers.

Although this percentage may appear modest, the effect is significant both economically and statistically, representing an annual increase of more than \$13 billion in total capex in the sample.

In addition, the theoretical model suggests that an increase in the degree of product portfolio homogeneity between a firm and its competitors leads to a trade-off. On the one hand, there is a greater significance of peer stock prices for the firm's manager. On the other hand, there is also an increase in the informativeness of the firm's stock for the manager due to a greater number of informed traders trading on it. The covariance between the firm's investments and the stock prices of its peers grows with diminishing scale factors, as demonstrated by my empirical research. Specifically, the standardized coefficient associated with the quadratic component is negative (-0.08%) and statistically significant (t-statistic of -4.40).

To the best of my knowledge, these findings are the first to demonstrate that the degree of product portfolio similarity boosts the informativeness of peers' stock prices and fosters learning from peers' stock price mechanisms by the firm's manager.

Furthermore (*Result 2*), in line with Foucault and Fresard (2014) I found that this effect diminishes with the quality of managerial information. When the manager has a lot of

⁶ Indeed, the private information obtained by the trader of company A will also be informative for trading on company B if A and B sell similar goods because they will have more correlated demands;

⁷ See *Text-Based Network Industries and Endogenous Product Differentiation* (2016);

private information, they rely less on peer stock prices to make investment decisions, reducing the covariance with peer stock prices.

To conclude, the theoretical model reveals that, in the managerial learning scenario, a high degree of product homogeneity does not always imply a decrease in the covariance between firm i 's investment and its own stock price.

In fact, this occurs only if the manager of firm A has poor internal information (*Result 3*) or if there is a lot of information on the market⁸ (*Result 4*) as supported by empirical evidence.

The results of my study add to the extensive body of research investigating the real effects of secondary financial markets⁹.

Specifically, More specifically, they complement the expanding literature on how stock prices influence a manager's internal investment decisions¹⁰, by studying how product diversification can be used by managers to protect the company against the imitation behavior by closely related peers. Additionally, they contribute to the literature about the effects of peers on a firm's investment decisions¹¹ focusing on the link between product portfolio diversification and the informativeness of peers' stock prices.

The remainder of the work is organized as follows. Section 2 describes the theoretical model which develops the empirical implications of the effects of product diversification on the managerial learning from peers' stock prices. Section 3 describes the data and the empirical methodology that I use to test the theoretical implications. Section 4 presents the main conclusions.

⁸ according to the order flow rule established in Section 2.1, the greater the degree of product portfolio homogeneity (δ), and the more the informed speculator on firm $-i$ that will invest in firm I , the more is the market information;

⁹ See Hayek (1945); Baumol (1965); Fama (1970); Grossman (1976); Hellwig (1980); Stein (1989); Bernanke and Woodford (1997); Hart and Zingales (2011); Bond and Goldstein (2015); Goldstein and Yang (2017); Siemroth (2019);

¹⁰ See Tobin (1969); Fama (1981); Barro (1990); Morck et al. (1990), Blanchard et al.(1993); Allen (1993); Stein (1996); Baker et al. (2003); Durnev et al. (2004); Chen et al. (2007); Campello and Graham (2013); Ozoguz and Rebello (2013); Foucault and Fresard (2014); Edmans et al. (2017); Dessaint et al. (2019); Vo (2021); Da Silva (2021);

¹¹ Gilbert and Lieberman (1987); Fresard (2010); Leary and Roberts (2012); Fracassi (2012); Dougal et al. (2015); Chen and Ma (2017); Bernard et al. (2020); Gordon et al. (2020); Wu et al. (2020); Rashid and Said (2021);

2. Theoretical Model

2.1 The structure of the model

The model is an extension of Foucault and Fresard (2014). We consider two firms A and B. At date 1, investors trade the stocks of the two firms on the market by determining their prices p_{A1} and p_{B1} . The manager of the firm A must determine whether or not to expand its' firm production capacity on the following date ($t=2$) before knowing the demand for its product.

Both firms' product demands and cash flows will be realized on date 3. At that time, the demand d_j for the firm j 's product might be High (H) or Low (L) with equal probability.

The two firms' demands might be more or less correlated depending on the degree of homogeneity (or similarity) of their product portfolio (δ^{12}) and the degree of correlation of the common shocks affecting the two companies (ρ), that is

$$\Pr(d_A=H \mid d_B=H) = \Pr(d_B=H \mid d_A=H) = \delta\rho$$

where $\delta\rho \neq \frac{1}{2}$. At date 3, the cash-flow of firm B can be High (θ_B^H) or Low (θ_B^L) depending on whether the demand for its product is high or low.

Conversely, because firm A's manager can decide to expand its production capacity at date 2, firm A's cash flow is the total of the cash flow of its existing assets plus the cash flow of its growth opportunity if the firm invests. We consider Σ_j the incremental revenues for firm A if it invests an indivisible amount equal to K .

In that case, at date 3, the cash-flow of firm A would be $\theta_B^H + I \times \Sigma_H$ where $I=1$ if firm A invests at date 2 (otherwise $I=0$). The net present value of firm A's investment possibility is $\Sigma_H - K$ if $d_A = H$, $\Sigma_L - K$ if $d_A = L$. Assuming that $\Sigma_H > K > \Sigma_L$ we can simplify the model setting $\Sigma_L = 0$.

At date 2, the manager of firm A observes stock prices realized at date 1 and observes a signal $s_m = \{H, L, \emptyset\}$ relates to the payoff of his growth opportunity. When $d_A=j$, $s_m=j$ with probability γ or $s_m=\emptyset$ (no signal) with probability $(1-\gamma)$. Specifically, γ measures

¹² if the value of δ is higher, it suggests that the competing firms have a greater similarity in their product portfolios and their demands are more closely aligned.;

the quality of "direct management information" (internal information), i.e., the probability that the manager has complete knowledge of the payoff of his growth opportunity. The expected value of firm A, after taking into account the manager's investment decision, is the sum of the expected cash flow of assets in place and the expected NPV of the growth opportunity, both of which are conditional on the information available to the manager at date 2, that is : $V_A(I) = E(\theta_A | s_m, p_{A1}, p_{B1}) + I \times E(NPV | s_m, p_{A1}, p_{B1})$.

Two assumptions are fundamentals in the models: the first one is that, if the manager had no information, he would not invest at date 2, i.e., the expected NPV of the growth opportunity is negative, that is: A.1 $E(NPV) = K \left(\frac{R_H}{2} - 1 \right) \leq 0$, where $R_H = \Sigma_H / K$ is the investment's yield.

The second one is that the correlation in demands for both firms is such that if the manager of firm A learns that demand for firm B is high, then he invests. That is: A.2 $E(NPV | d_B = H) = K(\delta \rho R_H - 1) > 0$ which implies $\delta \rho > 1/R_H > \frac{1}{2}$.

Following Foucault and Fresard (2014), in the stock market there are three types of investors: a) a continuum of risk-neutral speculators, b) liquidity traders with an aggregate demand z_j , uniformly distributed over $[-2, 2]$, and c) risk-neutral dealers. Speculators receive a signal $s_{ij} = \{H, L, \emptyset\}$. However, only a fraction π_j of speculators receives a perfect signal, i.e., $s_{ij} = d_j$, about the future demand for the product firm $j = \{A, B\}$. The remaining fraction of speculators, $1 - \pi_j$, observe no signal about the future demand of the firm j ($s_{ij} = \emptyset$).

After receiving her signal on stock j , a speculator can choose to trade one share of the stock of which it received the signal or not. Furthermore, the speculator relies on the similarities of the product portfolios of A and B¹³ and could decide to use the information obtained by the signal to also trade on a share of the firm j 's competitor. In this way, a cross-trading process takes place between the informed speculators of the two firms, which makes the model more realistic since a speculator with a perfect

¹³ therefore, observing the "δ" on the market. In fact, if it is complicated to observe the degree of correlation of the common shocks affecting the two companies (ρ) it is easier to observe their degree of the homogeneity of their products portfolio by reading their annual reports or by visiting their websites, for example;

signal on stock j is also partially informed about the payoff of the other stock and would trade both assets.

Let $x_j(s_{ij}) \in \{-1, 0, 1\}$ denote the demand of speculator i for stock j given the signal she obtained. Furthermore, once obtained the information on stock $-j$, the informed speculator $-i$ observes the homogeneity's degree of product portfolio between the firms j and $-j$ and will trade on it. Thus, let $x_{-j}(s_{-ij}) \in \{-1, 0, 1\}$ denote the demand of speculator $-i$ for stock j , f_j , that is the order flow for stock j , will be the sum of speculators and liquidity traders' net demand: $f_j = z_j + x_{ij} + \delta x_{-ij}$, where $x_{ij} = \int_0^1 x_{ij}(s_{ij}) di$ and $x_{-ij} = \int_0^1 x_{-ij}(s_{-ij}) di$. The price of stock j is determined based on the information present in the order flow: indeed, as in (Kyle, 1985), the dealers absorb the demand for the stock j at a price that makes the order flow break even. That is, $p_{A1}(f_A) = E(V_A(I^*) | f_A)$, and $p_{B1}(f_B) = E(\theta_B | f_B)$.

Let $\Delta p_j = p_{j1} - p_{j0}$ denote the change in price of stock j from date 0 to date 1, where, using the Law of Iterated Expectations, the stock prices of firms A and B at date 0 are $p_{A0}(I^*) = E(V_A(I^*))$ and $p_{B0}(f_B) = E(\theta_B)$.

2.2 Products portfolio similarity and the informativeness of peers' stock prices

In this section, I will show how product portfolio diversification affects the informativeness of peers' stock prices. To derive my empirical implications, I start to analyze the stock market equilibrium for firm B and then I solve for stock prices and optimal investment policy of firm A in equilibrium

2.2.1 The stock market equilibrium for firm B

The stock market equilibrium for firm B is as follows:

1. A speculator i buys stock B when she knows that demand for firm B's product is high ($x_{iB}^*(H) = +1$), sells it when she knows that demand for firm B's product is low ($x_{iB}^*(L) = -1$), and does not trade otherwise ($x_{iB}^*(\emptyset) = 0$);
2. A speculator $-i$ buys an amount of stock B when she knows that demand for firm A's product is high ($x_{-iB}^*(H) = +1$), sells it when she knows that demand for firm A's product is low ($x_{-iB}^*(L) = -1$), and does not trade otherwise ($x_{-iB}^*(\emptyset) = 0$). However, she buys only an amount of stock B depending on the degree of products portfolio homogeneity between A and B, δ ;

3. The stock price of firm B at date 1, $p_{B1}^*(f_B)$, is an increasing step function of investors' net demand for this stock, f_B . Thus, $p_{B1}^*(f_B) = \theta_B^H$ if $f_B > 2 - \pi_B - \delta\pi_A$, $p_{B1}^*(f_B) = \theta_B^L$ if $f_B < -2 + \pi_B + \delta\pi_A$, $E(\theta_B)$ if $-2 + \pi_B + \delta\pi_A < f_B < 2 - \pi_B - \delta\pi_A$.

The interpretation is as follows: if investor's net demand is relatively strong, that is $f_B > 2 - \pi_B - \delta\pi_A$, dealers infer speculators received a good signal about the demand for firm B's product.

Furthermore, they also deduce that the speculators who are informed of stock A, the direct competitor of stock B, received a good signal regarding the demand for firm A's product.

In some ways, this information confirms what dealers infer about firm B's demand, given that its direct competitor (with a homogeneous product portfolio) will similarly have a high demand for its product. Therefore, the stock price of firm B will be θ_B^H .

Similarly, but using the opposite logic, if the investor's net demand is relatively low, i.e. $f_B < -2 + \pi_B + \delta\pi_A$ (thus, both firm A and B's informed speculators received a bad signal about the demand of the products of their respective company), dealers infer that speculators received bad signals and the price of stock B will be θ_B^L .

For the intermediate realizations, dealers cannot infer the signals received by the speculators and the investors' net demand ($-2 + \pi_B + \delta\pi_A < f_B < 2 - \pi_B - \delta\pi_A$) will be not informative. Thus, for these realizations, the price of stock B is just equal to the unconditional expected cash flow of this firm.

Given that $\Delta p_j = p_{j1} - p_{j0}$, then $\Delta p_B = p_{B1} - p_{B0} = p_B - E(\theta_B)$ will be the change in the price of stock B from date 0 to 1.

To understand if the change in firm B's stock price is informative for the firm A's manager I compute the likelihood ratio, as in Foucault and Fresard (2014).

The likelihood ratio (LR) is the ratio between the probability that a positive change in B's stock price occurs between dates 1 and 0 when demand for firm A's product is high to the probability that a negative change in B's stock price occurs during the same period when demand for firm A's product is high.

If the change in the stock price of firm B is informative for the manager of firm A in predicting the demand for its product, the numerator is bigger than the denominator, i.e., the ratio is greater than one.

Using Proposition 1 I obtain the likelihood ratio as follows:

$$LR = \frac{Pr(\Delta P_B \geq 0 | d_A = H)}{Pr(\Delta P_B \leq 0 | d_A = H)} = \frac{1 - \frac{\pi_B}{2}(1 - \frac{\delta\rho}{2} - \frac{\delta\pi_A}{2})}{1 - \frac{\pi_B}{4}(1 + \delta\rho) - \frac{\delta\pi_A}{2}}.$$

It is easy to show that this ratio is greater than 1 only if $\delta\rho$ is greater than $\frac{1}{2}$.

This means that to be informative for firm A's manager, firm B not only must have productivity shocks highly correlated with that of firm A (that is, at least $\rho > \frac{1}{2}$) but also a high degree of products portfolio similarity¹⁴ (at least $\delta > \frac{1}{2}$). Furthermore, their product has to be greater than $\frac{1}{2}$.

According to A.2, we know that $\delta\rho$ is always more than $\frac{1}{2}$, thus, the LR is always greater than 1 implying that the change in firm B's stock price is truly informative about the demand for firm A's product.

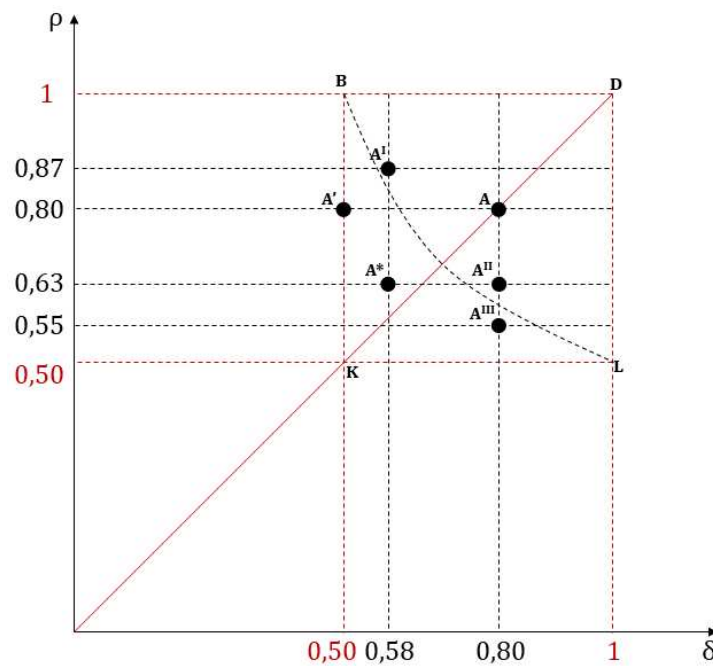
Moreover, this ratio increases in π_A , π_B , ρ and δ . According to these findings, the informativeness of firm B's stock price increases with the market information (π_A , π_B), the correlation of common shocks (ρ), and, most importantly, with the degree of products portfolio homogeneity (δ).

Interestingly, according to these results, the manager of firm B will be able to make changes in his stock price less informative to the manager of firm A by increasing the diversification of its product portfolio (i.e. by decreasing δ). This suggests that product portfolio diversification may be viewed as a valuable strategy for managers to defend themselves against the imitative strategies of their most direct competitors. This conclusion is novel and extends the findings of Foucault and Fresard (2014) by giving a role to product diversification, which is increasingly observed in markets (see Figure 1 for a graphic interpretation of the phenomenon).

¹⁴ It means that if firm B and firm A are in the same nation and so impacted by a strongly correlated common shock, but have significantly diverse product portfolios, a change in firm B's stock price is not useful for firm A's manager in obtaining new information about its product demand. Similarly, even if firm B and firm A have highly homogeneous product portfolios but are not affected by highly correlated common shocks (for example, because firm A is located in China and firm B is located in the United Kingdom), the change in firm B's stock price may be ineffective for firm A's manager;

Figure 1 – The effect of product portfolio homogeneity

The image below clearly exemplifies the role of product diversification. The sole variable in Foucault and Fresard's (2014) model that related the demands of firms A and B was the variable " ρ ", hence a change in company B's stock price was informative for firm A's manager only if " ρ " was larger than $\frac{1}{2}$. In my model, however, the demands of the two firms might be more or less correlated depending on the degree of homogeneity of their product portfolio (δ) and the degree of correlation of the common shocks impacting the two firms (ρ). By including the variable " δ " in the model, I allow that firm A's manager believes it is helpful to observe not only the firms with which he has a highly correlated demand shock, but also the companies with which he has a more comparable product portfolio. This means that the change in firm B's stock price is informative for firm A's manager only if both " ρ " and " δ " assume high value. Specifically, if their product exceeds $\frac{1}{2}$. In fact, if we consider two public firms, A and B, that have very different sales markets (i.e., firm A sells its product primarily in Australia and firm B sells its product primarily in Canada) and, thus, most likely low correlated demand shocks, they will consider each other a peer only if they have a high similar product portfolio (for example, both firms sell winter coats). Otherwise, the firm B's change in stock price would not be informative for firm A's manager. The plane limited by the points L, B, and D determines the combination of " ρ " and " δ " that makes informative the change in firm B's stock price for company A's manager in the figure. If firm A and firm B have the same mix of " ρ " and " δ " as in point A*, the change in stock B's price will not be informative to firm A's manager. Keeping the level of " ρ " constant, if company A makes its product portfolio more comparable to that of firm B (the combination A''), then the change in firm B's stock price becomes informative for firm A's manager. Similarly, at a constant degree of product portfolio similarity (δ), an increase in the correlation of demand's common shocks from A* to A' makes the change in firm B's stock price informative for firm A's manager (this is the case of two firms that sell their product in a similar sales market despite having a low degree of product portfolio similarity). Indeed, despite a high level of correlation between common shocks to demand, the combination A' between company A and firm B will not make a change in firm B's stock price informative for firm A's manager due to the low value of.



2.2.2 The stock market equilibrium for firm A

The stock market equilibrium for firm A is as follows:

1. A speculator i buys stock A when she knows that demand for firm A's product is high ($x_{iA}^*(H)=+1$), sells it when she knows that demand for firm A's product is low ($x_{iA}^*(L)=-1$), and does not trade otherwise ($x_{iA}^*(\emptyset)=0$);
2. A speculator $-i$ buys an amount of stock A when she knows that demand for firm B's product is high ($x_{-iA}^*(H)=+1$), sells it when she knows that demand for firm B's product is low ($x_{-iA}^*(L)=-1$), and does not trade otherwise ($x_{-iA}^*(\emptyset)=0$). However, she buys only an amount of stock A depending on the degree of products portfolio homogeneity between A and B, δ ;
3. The stock price of firm A at date 1, $p_{A1}^*(f_B)$, is an increasing step function of investors' net demand for this stock, f_A . Thus, $p_{A1}^*(f_A)=\theta_A^H$ if $f_A > 2-\pi_A-\delta\pi_B$, $p_{A1}^*(f_A)=\theta_A^L$ if $f_A < -2+\pi_A+\delta\pi_B$, $E(\theta_A)$ if $-2+\pi_A+\delta\pi_B < f_A < 2-\pi_A-\delta\pi_B$.

As for stock B, investors' net demand for stock A, f_A , affects its stock price and is more informative about the future demand for firm A's product the greater the number of informed speculators (π_A and π_B) and the product homogeneity (δ).

Remember that $p_{A1}(f_A)=E(V_A(I^*)|f_A)$. Using this equation with Proposition 2 I obtain the following:

$$P_{A0}(I^*)=E(E(V_A(I^*)|f_A))=E(P_{A1}(f_A))=E(\theta_A)+\frac{1}{2}(\gamma + (1 - \gamma))[(\frac{\pi_A}{2} + \frac{\delta\pi_B}{4}) + (\frac{\pi_B}{2} + \frac{\delta\pi_A}{4})(1 - (\frac{\pi_A}{2} + \frac{\delta\pi_B}{4}))](\Sigma_H-K)$$

where the first term ($E(\theta_A)$) is the unconditional expected value of the firm A's assets in place and the second term is the unconditional expected value of its growth opportunity. If $-2+\pi_A+\delta\pi_B < f_A < 2-\pi_A-\delta\pi_B$, the stock price of firm A is not informative, and it decreases the likelihood that the firm A will invest. Thus, it follows that $p_A^L \leq p_A^M \leq p_{A0}(I^*) \leq p_A^H$.

From these inequalities, we can deduce that when the manager doesn't receive direct managerial information (i.e. $s_m=\emptyset$) he invests: i) if and only if the change in the price of stock A from date 0 to date 1, Δp_A , is positive (it means that net investors' demand is high and it indicates a high demand of firm A's product); ii) alternatively, if and

only if the change in the price of stock B is positive and the change in the price of stock A is moderately negative (i.e., $p_A = p_A^M \leq p_{A0}(I^*)$).

Ergo, a positive change in the stock price of firm B provides a strong signal regarding future demand for the product sold by firm A (since they are peers with correlated demands) that compensates for the tiny decline in the stock price of firm A (that is p_A^M and, thus, uninformative). As a consequence, we infer that firm A's investment policy is also determined by the price of stock B, implying that it is affected by both its own stock price and the price of its peer's stock (B).

2.3 Empirical implications

In this section, I will derive theoretical predictions to test in the empirical model using the data obtained in section 2.2 in this part.

If the manager uses information gathered from stock prices, we should expect to observe a positive covariance between investments and the stock prices of peers. Yet, this correlation might also result from a potential covariance between managers' information about their growth opportunities.

Thus, to strongly support the learning from peers' stock prices hypothesis, as in Foucault and Fresard (2014), I will compare the effects of variables (π_A , π_B , δ , ρ , and γ) in three different scenarios: 1) no managerial learning; 2) managerial learning only from its own stock price; 3) managerial learning from both its' stock prices and that of its peers. To simplify notations, we denote $(\theta_j^H - \theta_j^L)/2$ by σ_j and $(\sigma_A + (\Sigma_H - K)/2)$ by σ_A^H .

2.3.1 No managerial learning

In this section, I examine what happens when firm A's manager does not use the information contained in the stock prices.

This might be because she has previously been informed about its growth opportunities, thus she does not need to obtain new information from the markets (that is, the scenario where $\gamma=1$), or because she does not know (or cannot comprehend) that stock prices include relevant information.

Therefore, the manager of the firm A will determine her optimal investment policy just based on her private information: thus, she invests if $s_m=H$ and doesn't invest otherwise ($s_m=L$ or $\emptyset$).

In this scenario, the price of stock B does not change since it does not depend on the investment policy of firm A¹⁵. On the other hand, the price of stock A differs from that given in section 2.2.2 given that it depends on the investment policy of firm A. The covariance between firm A's investments and stock prices are the follows:

COROLLARY 1 (No managerial learning case). In the case of no managerial learning the covariance between firm B's stock price and firm A's investments is

$$Cov_{NO}(I, p_{B1}) = \frac{\gamma \sigma_B (\pi_B + \delta \pi_A) (2\delta \rho - 1)}{4}.$$

This covariance is always positive since A.2 implies that $\delta \rho > \frac{1}{2}$. It increases with (i) the quality of managerial information (γ), (ii) the fraction of informed speculators in both stock A and stock B (π_A and π_B), and (iii) the correlation in common shocks demand for the products of firms A and B (ρ). Moreover, it increases with the degree of products portfolio similarity (δ) solely if $\rho \geq \frac{\pi_A}{2(2\pi_A\delta + \pi_B)} = \rho'$.

That is, the covariance between firm A's investment and firm B's stock price will not always increase in δ in the case of "No Managerial Learning". The covariance will increase in δ if $\rho > \rho'$. Conversely, there will be a switch of its effect if $\rho < \rho'$ (i.e., the covariance will decrease in δ).

In reality, if δ grows, two distinct effects are activated: (i) an increase of δ implies an increase on the homogeneity's degree of products portfolio, which implies managers and speculators will observe more correlated signals and a higher covariance between firm A's investment and firm B's stock prices; (ii) an increase of δ implies an increase on the stocks' demand, which increase the market information¹⁶. In this case, if firm A's manager does not observe market prices, she will lose a greater amount of information. Thus, when $\rho > \rho'$ (i.e., when the demands' common shocks are more

¹⁵ thus, it will be that given in section 2.2.1;

¹⁶ Remember that the market information is equal to $f_A + f_B$. A higher δ generates, all things being equal, a higher f_A and f_B ;

correlated) the effect (i) prevails over the effect (ii); it implies an increase of the covariance between firm A's investment and firm B's stock price.

Conversely, when $\rho < \rho'$ the effect (ii) prevails over the effect (i) (i.e., when the demands' common shocks are less correlated) and the covariance decrease with increasing degree of products portfolio's homogeneity¹⁷.

Furthermore, the covariance between the price of stock A and the investment of firm A is:

$$Cov_{NO}(I, p_{A1}) = \frac{\gamma(\pi_A + \delta\pi_B)(2\sigma_A + \gamma(\Sigma_H - K))}{2}.$$

This covariance is likewise positive and grows with i) the quality of managerial information (γ), (ii) the fraction of informed speculators in both stock A and stock B (π_A and π_B), and (iii) the degree of products portfolio's similarity (δ).

That is, the covariance between firm A's investment and the price of its stocks increases with the degree of products portfolio's similarity between firm A and B. This is because the closer the δ is to 1, the more informed speculators¹⁸ will invest in firm A stocks, and the stronger will be the correlation between the market information and that available to the manager (effect of cross-investment¹⁹). Thus, even in the absence of managerial learning, the investment of firm A is correlated with its peers' stock price and its own stock price since, actually, the signals received by the manager and the speculators are correlated. But not only, the greater the degree of products portfolio's homogeneity (δ) and the quality of managerial information (γ) the greater will be that correlation because both variables strengthen the correlation between the signals of the manager and the speculators²⁰.

2.3.2 Narrow managerial learning

In this section, I explore the case wherein firm A's manager is only concerned with the information contained in his own stock price. This might be due to the fact that the

¹⁷ That is, if $\rho < \rho'$ the positive effect generated by the increase in the correlation of the signals between managers and speculators is more than offset by the negative effect generated by the loss of information;

¹⁸ $\pi_A + \delta\pi_B$;

¹⁹ This effect is not present on the baseline model of Focault and Fresard (2014);

²⁰ Focault and Fresard (2014) called this source of covariation as “correlated information” channel;

price of stock B is uninformative, or because the manager of firm A is uninformed that this price is informative.

As in section 2.3.1, the price of stock B is not affected by the decisions of the firm A's manager, thus it will be that given in section 2.2.1. Instead, the stock price of firm A influences its manager's investment choice, and he will decide to invest based on his internal signal and the price level of his stocks.

That is, he optimally invests if he received a good signal about the future demand of his products ($s_m=H$) or, if his stock price is high ($p_A=p_A^H$). Otherwise, he does not invest. I obtain the following results:

COROLLARY 2 (Narrow managerial learning case). In the case of narrow managerial learning in which firm A's manager only uses information contained in the price of his stock, the covariance between the price of stock B and the investment of firm A is

$$Cov_{NARROW}(I, p_{B1}) = Cov_{NO}(I, p_{B1}) + \frac{(1 - \gamma)(\frac{\pi_B}{2} + \frac{\delta\pi_A}{2})(\frac{\pi_A}{2} + \frac{\delta\pi_B}{2})\sigma_B(2\delta\rho - 1)}{2}$$

As in the previous case, the covariance is positive because of A.2. Moreover, this covariance increases with (i) the quality of managerial information (γ), because it implies that firm A's manager has more correlated information with speculators²¹, (ii) the number of informed speculators (π_A and π_B), and (iii) the degree of products portfolio similarity (δ).

In fact, in this case the manager also observes the price of his stock prices on the market. The greater the δ , the greater the number of firm B's informed speculators who will invest in firm A's stock price and, thus, the greater the influence of them on the firm A's manager investment decision. This leads to a greater covariance between the firm B's stock price and the investments of firm A.

Furthermore, the covariance between the price of stock A and the investment of firm A is also positive and given by

²¹ See section 2.3.1;

$$Cov_{NARROW}(I, p_{A1})$$

$$= Cov_{NO}(I, p_{A1}) + \frac{(2 - (1 - \gamma)(\frac{\pi_A}{2} + \frac{\delta\pi_B}{2}))(\frac{\pi_A}{2} + \frac{\delta\pi_B}{2})(1 - \gamma)\sigma_A}{2}$$

This covariance decreases with (i) the quality of managerial information (γ), since if γ increases the manager will put less weight to the signals coming from the market and more to his internal signal, (ii) the fraction of informed speculators in both stock A and stock B (π_A and π_B). Furthermore, the covariance increases with (iii) the degree of products portfolio's homogeneity (δ).

The reason is as follows: a rise in δ suggests that a greater number of informed speculators from firm B will invest in firm A's stock price. The management of firm A is aware that a greater δ indicates more market information, and hence will rely more on the price of his own shares.

In this scenario both the covariances between firm A's investments and the price of firm B's stock price and its own stock price are greater than in the case of "No Managerial Learning".

Actually, in this case the stock price of firm A affects the manager investment decision constituting an additional source of covariation between investment and the firm's stock price, captured by the second components in the two expressions above.

In both situations, these learning channel-specific components increase with δ . In fact, a higher δ implies more market information and more correlated information between managers and speculators, resulting in larger covariances of stock prices with firm A's investment.

Conversely, the effects of an increase in γ is different on the two covariances: in the first one ($Cov_{NARROW}(I, p_{B1})$), it leads to a more correlated information between firm A's manager and speculators that increase the common information contained in the firm B's stock price and in the firm A's manager signal. Thus, the covariance increases. In the second one ($Cov_{NARROW}(I, p_{A1})$), it leads to a lower covariance since the firm A's manager rely less on his own stock price.

2.3.3 Managerial learning from peers' stock price

In this last scenario, the manager of firm A knows that the market's stock prices contain information that should complete her informative set. In fact, the markets aggregate information owned by a lot of traders and provide useful signals about, for example, the state of the economy or the prospects of the industries. Thus, in this case the investment decision of the firm A's manager is affected by both her firm's stock price and that of her peers. The results are as follows:

COROLLARY 3. In the "Learning from peers' stock price" scenario the covariance between the investment of firm A and the stock price of firm B is

$$\begin{aligned} & Cov_{PEER\ LEARNING}(I, p_{B1}) \\ &= Cov_{NARROW}(I, p_{B1}) + \frac{(1 - \gamma)(1 - \frac{\pi_A}{2} - \frac{\delta\pi_B}{2})(\frac{\pi_B}{2} + \frac{\delta\pi_A}{2})\sigma_B}{2} \end{aligned}$$

It is always positive since for A.2 $\delta\rho > \frac{1}{2}$ and $Cov_{NARROW}(I, p_{B1}) > 0$. Furthermore, since the second term is always positive it implies that in this case the firm A's investment and firm B's stock price covary more strongly relative to previous case. In fact, contrary to the "Narrow managerial learning" case now the price of stock B is a determinant of firm A's manager investment decision. Furthermore, this covariance increases with the degree of products portfolio similarity (δ) while it decreases with the quality of managerial information (γ). It is not univocal the effect of the increase of the fraction of both informed speculators in stock B and stock A (π_B and π_A). In fact, only if the product between δ and ρ is large enough ($\delta\rho > \delta\rho'$), then the increase in both firm B's and firm A's informed speculators will generate an increase in the information of the firm B's stock price greater than that of firm A. This will result in a higher weight that the manager of firm A will place to the price of stock B. Thus, only in that case the covariance would increase.

Additionally, the covariance between the price of stock A and the investment of firm A is:

$$\begin{aligned}
Cov_{PEER LEARNING}(I, p_{A1}) \\
&= Cov_{NARROW}(I, p_{A1}) \\
&= \frac{(1 + (1 - \gamma)(1 - \frac{\pi_A}{2} - \frac{\delta\pi_B}{2}))(\frac{\pi_B}{2} + \frac{\delta\pi_A}{2})(\frac{\pi_A}{2} + \frac{\delta\pi_B}{2})(1 - \gamma)\sigma_A}{2}
\end{aligned}$$

It is simple to demonstrate that the covariance between the investment of firm A and the stock price of firm A is always positive. But, unlike in the previous cases, the effects of the variables on this covariance are not unique.

The reason is that, when she learns from all stock prices, the manager of firm A has three sources of information: (i) direct managerial information, (ii) his stock price, (iii) the stock price of its peers. As a result, a substitution effect is generated between these sources of information.

To begin, the effect of an increase in the fraction of informed speculators in stock A (π_A) depends on the degree of products portfolio's homogeneity (δ). That is, if δ is greater enough ($\delta > \delta'$) a rise in π_A causes an increase in the informativeness of the price of stock B that is greater than the price of stock A, resulting in a decrease in the covariance between the investment of firm A and its stock price²². Conversely, the covariance increase.

Rather, the effect of an increase in the fraction of informed speculators in stock B (π_B) is determined by the quality of managerial information (γ). If γ is greater than 0.55 (γ'), the manager of firm A will place more emphasis on the internal information and less emphasis on both his peer's stock price and his own stock price (substitution effect). This covariance decreases as the manager relies less on his own stock price. Nevertheless, as the manager relies less on his peer's stock price, this covariance increases. Thus, when $\gamma > \gamma'$ the second effect is stronger than the first and $Cov_{PEER LEARNING}(I, p_{A1})$ increases with an increase in the fraction of informed speculators in stock B (π_B), and vice versa.

Furthermore, the influence of managerial information quality (γ) depends on the amount of the information available on the market. If it is high, that is the values of

²² This is consistent with what I find in Section 2.3.3 about the effect of an increase in π_A and π_B on $Cov_{PEER LEARNING}(I, p_{B1})$;

π_A, π_B and δ are high, an increase in γ indicates an increase in this covariance because, as previously explained, the manager will rely less on his peer's stock price.

Finally, if the quality of managerial information (γ) is low (i.e., less than 0.5), increasing the degree of products portfolio similarity (δ) results in a decreased covariance between the firm A's investment and firm A's stock price. In fact, when γ is low, the manager is more influenced by his peer's stock price, and an increase in δ creates a higher additional information effect on his peer's stock price rather than on the price of his share²³. Conversely, if γ is higher than 0.5, the covariance increases with an increase in δ .

2.4 Summary of the main theoretical results

In this section, I summarize the important findings from the previous sections. The crucial finding from analyzing the "learning from stock prices" mechanism that influences managers' decisions about their investment plans is that the degree of product portfolio similarity (δ) plays a significant role. My research reveals that a smaller product portfolio diversification leads to greater informativeness of peers' stock price changes for managers observing the market. I demonstrated that the covariance between the investment of a firm (I_A) and its peers' stock price (p_B) increases with the degree of products portfolio's similarity (δ), but at a diminishing marginal return on the increase in the stock prices of peers (*Result 1*). Consequently, product diversification is a critical component of corporate strategy. In fact, managers who do not implement a product portfolio diversification policy are more likely to face higher competition particularly from smaller peers who rely on market prices to obtain information they would not otherwise have, such as industry's prospective dynamics. Furthermore, this covariance decreases with the quality of managerial information (γ) (*Result 2*).

The inclusion of the homogeneity's degree of the products portfolio in the model generates a more complex dynamic. In fact, the increase in δ does not necessarily imply

²³ Indeed, since $f_A = Z_A + x_{Aj} + \delta x_{Bj}$ and $f_B = Z_B + x_{Bj} + \delta x_{Aj}$ an increase in δ leads to both an higher information on stock A and B. However, when the quality of managerial information is low the effect on stock B is greater than that of stock A. In this case, a higher value of δ leads to a lower covariation between firm A's investment and its' stock price;

a reduction in the covariance between I_A and p_A ; rather, this only occurs when the manager of firm A has a lower quality of internal information (γ) (*Result 3*). In cases where the internal information is of high quality, an increase in δ generates an increase in information available on the market (due to the cross-trading of informed speculators) which leads to an increase in covariance.

Furthermore, I found that uniquely in the learning scenario, when there is a high amount of information available in the market, an increase in the quality of managerial internal information results in a higher covariance between firm (I_A) and its own stock price (p_A) (*Result 4*). This is because the manager of firm A places more importance on internal information, and less on both their own stock price and their peers' stock price.

In the empirical analysis that follows, I will examine the primary findings of the model, by performing a regression analysis of a company's investment on both its stock price, its' peers stock price and an interaction variable that account for the effect of product portfolio similarity.

3. Data description and empirical model

3.1 Dataset construction and descriptive statistics

My dataset is built on a sample of U.S. public firms. Since I want to test if product similarity matters when managers observe the market's stock prices, I used data from the Hoberg and Phillips's dataset developed in 2016.

Specifically, in each year, they compute a measure of product similarity for every pair of firms by comparing the product descriptions from the company 10-K forms. The measure ranges between 0% and 100% with respect to the relative number of words that two firms share in their product description. The more the measure is near to 100% the more the two firms have a similar products portfolio. Then, they identified the TNIC peers of each firm by setting a threshold of minimum similarity and taking only the peers with a similarity's coefficient greater than the threshold. To conclude, they computed the score I have in my dataset by computing the amount by which the pairwise score exceeded the similarity threshold for being included in the TNIC

database²⁴. I used this measure as proxy of the product portfolio homogeneity between the two competing firms.

Then, using the GVKEY codes of each company I matched these with financial data obtained by Eikon Refinitiv. I take the firm-year observations for each of these variables from 2002 to 2019 based on the data available on Eikon Refinitiv.

Because of the differences in regulations, I exclude firms in the utilities (SIC codes 4000-4999) and banking industries (SIC codes 6000-6999), as well as firm-year data with negative sales. To sum up, my sample consists of an unbalanced panel of 89.541 firm-year observations (each of them pairs two different competitor firms) of 712 distinct firms going from 2002 to 2019.

Table 1 shows that the average number of peers per firm is 28 and the median is 23. That is, for the time period considered, the average number of different peers I pair for each firm is 28.

Nevertheless, this does not imply that I match one firm with all 28, as it is possible that one or more of these were not yet founded in a given year, but rather that I pair that company with 28 separate peers during the whole studied time.

As baseline dependent variable I used the Capex Ratio, computed as capital expenditures at time t divided by lagged Total Assets. According to Mitton (2022), this is the most common dependent variable used in the top ten financial journals when studying investment framework. Its average value in my sample is 4,55%.

The other control variables I used in the empirical approaches are: *Tobin Q*, as a proxy for firm stock price, computed as the book value of assets minus the book value of equity plus the market capitalization, scaled by lagged book value of assets, *Size*, as proxy of the size of the firms, computed as the logarithm of total assets, and the *Leverage*, as proxy of the leverage of the firm, computed as the ratio between long-term debt at time t and its lagged total assets.

The average degree of portfolio homogeneity (*Similarity*) is 3,65%. The two tables that follow give descriptive data as well as a definition of the variables utilized in the models.

²⁴ Thus, my dataset has composed by rivals that are "nearer" rivals than others;

Table 1a – Summary statistics

This table summarizes the main variables used in the empirical analysis by presenting, for each variable, the mean, the first and the third quartiles, the

Variables	Mean	SD	p25	p50	p75	Min	Max	N
<i>Capex Ratio</i>	4.553	5.252	1.386	2.868	5.558	0.019	29.743	46,563
<i>Size</i>	6.939	2.175	5.278	6.907	8.513	2.419	11.67	61,652
<i>Tobin Q</i>	2.183	2.007	0.984	1.664	2.698	0.083	11.76	61,652
<i>Leverage</i>	0.174	0.209	0	0.120	0.266	0	1.049	61,652
<i>Capex on Sales</i>	14.593	46.422	2.206	4.007	7.823	0.052	390.997	46,563
<i>Dummy divers.</i>	0.499	0.500	0	0	1	0	1	61,692
<i>Dummy inform.</i>	0.119	0.323	0	0	0	0	1	61,692
<i>Similarity</i>	0.045	0.041	0.016	0.035	0.065	0	0.856	61,692
<i>Manager inform.</i>	10.685	55.850	-0.081	0.137	0.768	-0.935	463.301	61,692
<i>Price inform.</i>	0.089	1.880	-1.092	0.097	1.286	-10.042	8.862	61,692
<i>Total assets (in millions)</i>	7,761	19,356	194.564	999.375	4,980	10.927	117,565	61,692
<i># of peers</i>	28	21	10	23	40	6	45	61,692
<i># of single firms</i>	712							

Table 1b – definition of the variables

Variable	Definition	Source
<i>Capex Ratio</i>	the ratio between the capex of the firm in year t and its lagged total assets	Refinitiv Eikon
<i>Capex /PP&E</i>	the ratio between the capex of the firm in year t and its lagged property, plant, and equipment	Refinitiv Eikon
<i>Capex /Sales</i>	the ratio between the capex of the firm in year t and its lagged sales	Refinitiv Eikon
<i>Size</i>	the logarithm of the book value of assets in year t	Refinitiv Eikon
<i>Leverage</i>	the ratio between the long-term debt and the total assets of the firm in year t	Refinitiv Eikon
<i>Tobin Q</i>	the ratio between the sum of the book value of assets plus the market value of equity minus the book value of equity of the firm in year t and the book value of equity of the firm in year t	Refinitiv Eikon
<i>Similarity</i>	the degree of the product portfolio similarity, computed by Hoberg & Phillips (2016) as score for every pair of firms by parsing the product descriptions from their 10-Ks	Hoberg-Phillips datalibrary
<i>Dummy divers.</i>	a dummy equal to one if the <i>Similarity</i> between firm i and -i is greater than that of the median in their industry in that year t.	Hoberg-Phillips datalibrary
<i>Manager inform.</i>	the annual average of the one-month return of the firm i's insider transactions	Refinitiv Eikon
<i>Price inform.</i>	computed as in Roll (1988), that is $\ln((1-R2i,t)/R2i,t)$ where the $R2i,t$ is that from the regression in year t of firm i's weekly returns on market returns and the peers' value-weighted portfolio returns.	Refinitiv Eikon

3.2 Empirical methodology

To empirically show the impact of products portfolio diversification on the “learning from peers’ stock price” mechanism I made two steps: firstly, I replicated the regression made by Foucault and Fresard (2014) to check if in my sample also there is a positive covariation between a firm’s investment and the stock price of its peers as well as its own stock price.

Hence, in a second step, I test the prediction I found in theoretical model specifically in the learning scenario by including an interaction variable in my baseline regression between the Tobin’s Q and the similarity’s coefficient.

In the first step I estimated the same regression Foucault and Fresard (2014) used in their paper with a fixed-effects model (within estimator):

$$N.1 \quad I_{i,t} = \alpha_i + \eta Q_{-i,t-1} + \beta Q_{i,t-1} + \varphi X_{-i,t-1} + \kappa X_{i,t-1} + \varepsilon_{i,t}$$

where α_i are the firm pair fixed effects. The subscripts i,-i and t represent, respectively, firm i (i.e., firm A in the model), firm -i (i.e., firm B in the model), and the year. In the first step I aim to confirm the effect of explanatory variables $Q_{-i,t-1}$ and $Q_{i,t-1}$, that is the Tobin’s Q of firm -i and i in year t-1 (that I used as a proxy of the stock prices of the two firms), to the dependent variable, $I_{i,t}$, that is the ratio of capital expenditure in that year scaled by lagged fixed assets, found in Foucault and Fresard (2014) in a different sample going from 2002 to 2019.

Moreover, the two vectors $X_{-i,t-1}$ and $X_{i,t-1}$ contain control variables about the two firms that are known to affect firm’s investment decisions and that I detailed in Section 3.1.

In all the regressions I scaled all independent variables by their standard deviation to obtain estimated coefficients that are directly informative about the economic significance of the effects they have.

That is, the coefficients measure the change in firm i’s investment for a one standard deviation increase in the independent variables.

Additionally, this means that the coefficient associated to $Q_{-i,t-1}$, that is η , is by definition the covariance between firm i’s investment and firm -i’s stock price.

In the second step, I augmented the baseline specification as following:

$$\text{N.2 } I_{i,t} = \alpha_i + \eta_0 Q_{-i,t-1} + \eta_1 (Q_{-i,t-1} \times \lambda_{i,-i,t}) + \eta_2 (Q_{-i,t-1} \times \lambda_{i,-i,t})^2 + \\ \eta_3 \lambda_{i,-i,t} + \beta Q_{i,t-1} + \varphi X_{-i,t-1} + \kappa X_{i,t-1} + \varepsilon_{i,t}$$

where $\lambda_{i,-i,t}$ represents a dummy variable (*Dummy divers.*) that interact with my main control variable ($Q_{-i,t-1}$) to consider in the model the products portfolio similarity between firm i and $-i$ at time t . My aim is to show that firm i 's manager learns more from his peers with more homogeneous products portfolio.

Thus, to build the dummy λ (*Dummy divers.*) I computed the average of the similarity's coefficient for each year and for each 4D NAICS code.

Then, if the firm i and $-i$ had a similarity's coefficient greater than the median in that year of the firms belong to the same firm i 's 4D NAICS code thus $\lambda = 1$; otherwise, $\lambda = 0$.

Moreover, I include a quadratic term of my interaction variable $((Q_{-i,t-1} \times \lambda_{i,-i,t})^2)$ to test my theoretical model's result which implies a grow, at decreasing scale factors, of the effect of an increase in δ on the covariance between the firm A 's investment and its peer's stock price.

As in the above specifications, α_i are the firm pair fixed effects. $X_{-i,t-1}$ and $X_{i,t-1}$ contain control variables about the two firms that are known to affect firm's investment decisions.

Finally, in order to empirically address the *Result 2, 3 and 4*, I performed the following fixed-effects model (within estimator):

$$\text{N.3 } I_{i,t} = \alpha_i + \beta_0 Q_{i,t-1} + \beta_1 (Q_{i,t-1} \times \varphi_{i,t-1}) + \beta_2 \lambda_{i,-i,t} + \beta_4 Q_{-i,t-1} + \\ \beta_5 X_{-i,t-1} + \beta_6 X_{i,t-1} + \varepsilon_{i,t}$$

Where $\varphi_{i,t-1}$ is the proxy for the model's parameters that we want to test in *Result 2, 3 and 4*, and α_i are the firm pair fixed effects. β_1 is the coefficient that we are interested in, because it gives us the additional effect of the parameter we are testing on the

covariance between the firm i 's investments and its stock price (β_0 is the covariance when this effect is equal to 0).

As in the previous specifications, $X_{-i,t-1}$ and $X_{i,t-1}$ contain control variables about the two firms that are known to affect the firm's investment decisions and all the independent variables are scaled by their standard deviation to obtain estimated coefficients that are directly informative about the economic significance of the effects they have.

I winsorized all control variables at both 1% and 99%

3.3 Empirical results

To begin, I replicated the model of Foucault and Fresard (2014). The results I obtain are in Table 2.

I show that my dataset follows their findings despite not using "standardized" stock prices like the two authors did in their work and not considering the same period.

Particularly, as shown in Column (1) of the table above, a firm's investment sensitivity to its peers' Q is positive and statistically significant.

To be more specific, a one standard deviation increases in peers' Tobin's Q implies a 0,09% increase in its investment (t-statistic of 2,91).

These results are robust even when various base model specifications are applied. I modified the dependent variable in Columns (2) and (3) by utilizing the same set of control variables and model as in Column 1.

Even though these findings are consistent with those of the two authors, the economic magnitudes differ.

This might be because they utilized standardized stock prices in their study, whereas I use non-standardized stock prices, and because they matched each firm I with a group of TNIC peers, whereas I pair each firm with only one peer.

Furthermore, the relationship between a firm's own Tobin's Q and its investment is positive and highly significant indicating that a one standard deviation increase in Tobin's Q of firm i is associated with a 87,90% increase in its investment (with a t-statistic of 21,47).

Table 2 – The relationship between the investment ratio of firm i and its peers' stock prices

This table reports the estimates obtained using a fixed effects model regression of the investment ratio of firm i at time t, on peers' stock prices and controls. I used three different dependent variables in these specifications: In Column (1), I used the ratio of firm i's Capex in year t to its lagged total assets, in Column (2), I used the ratio of firm i's Capex in year t to its lagged book value PP&E, and in Column (3), I utilized the ratio of firm i's Capex in year t to its lagged sales. Tobin Q is the proxy of firm i and -i's stock prices computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t. Size is the natural logarithm of total assets of firm i at time t. Leverage is the ratio of total debt on total assets of firm i at time t. In Columns (4) to (6) I used a first-difference fixed effects model to address endogeneity issues. All control variables are winsorized at both 1% and 99% and standardized. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm level. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variable	Capex Ratio _{i,t} (2)	Capex /PP&E _{i,t} (3)	Capex /Sales _{i,t} (4)	D.Capex Ratio _{i,t} (1)	D.Capex /PP&E _{i,t} (5)	D.Capex /Sales _{i,t} (6)
<i>Tobin Q</i> _{-i,t}	0.0910*** (0.0312)	0.324** (0.149)	3.746* (2.108)			
<i>Tobin Q</i> _{i,t}	0.873*** (0.0407)	2.921*** (0.168)	5.721*** (1.951)			
<i>D.Tobin Q</i> _{-i,t}				0.0587* (0.0307)	0.426*** (0.163)	1.122* (0.607)
<i>Capex Ratio</i> _{-i,t}	0.392*** (0.0696)					
<i>Size</i> _{i,t}	-0.979*** (0.166)	7.611*** (0.744)	-34.59*** (7.245)			
<i>Size</i> _{-i,t}	-0.00271 (0.152)	0.315 (0.537)	7.123 (5.424)			
<i>Leverage</i> _{i,t}	-0.581*** (0.0381)	-2.147*** (0.124)	-0.385 (2.024)			
<i>Leverage</i> _{-i,t}	-0.0749* (0.0418)	0.0176 (0.144)	0.758 (1.516)			
<i>Capex/PP&E</i> _{-i,t}		0.227** (0.103)				
<i>Capex Sales</i> _{-i,t}			-0.572 (1.478)			
<i>D.Tobin Q</i> _{i,t}				0.381*** (0.0471)	0.434* (0.226)	11.65*** (1.102)
<i>D.Capex Ratio</i> _{-i,t}				0.106** (0.0491)		
<i>D.Leverage</i> _{i,t}				-0.310*** (0.0314)	-1.344*** (0.196)	-0.496 (0.764)
<i>D.Leverage</i> _{-i,t}				-0.0157 (0.0347)	-0.0579 (0.193)	-0.247 (0.681)
<i>D.Size</i> _{i,t}				-5.169*** (0.276)	8.123*** (1.031)	4.138 (4.508)
<i>D.Size</i> _{-i,t}				0.308 (0.189)	2.488*** (0.836)	2.739 (2.912)
<i>D.Capex/PP&E</i> _{-i,t}					0.0184 (0.102)	
<i>D.Capex Sales</i> _{-i,t}						-0.342 (0.414)
<i>Constant</i>	8.158*** (0.647)	-7.209*** (2.597)	95.59*** (23.42)	-1.346 (0.905)	-7.906*** (2.659)	-3.364** (1.558)
Observations	35,578	35,465	34,912	27,102	27,038	34,612
R-squared	0.094	0.083	0.013	0.187	0.154	0.106
Firm Pair FE	Yes	Yes	Yes	No	No	No
S.E. Cluster	Firm Pair	Firm Pair	Firm Pair	Firm Pair	Firm Pair	Firm Pair

The standard errors I used to compute the t-statistics are adjusted for heteroskedasticity and clustered at the firm pair level.

In Column (2), I used the ratio of firm i's Capex in year t to its lagged book value property, plant, and equipment as the dependent variable.

In Column (3), on the other hand, I utilized the ratio of firm i's Capex in year t to its lagged sales as the dependent variable.

The dependent variable has a positive and statistically significant relationship with both Tobin $Q_{-i,t}$ coefficients.

To address the conventional endogeneity issues, I regress the model with a first-difference fixed effect model in Columns (4) to (6) as an additional robustness check, using a pooled OLS estimation for a regression of the differenced variables.

The coefficients associated with the variable $D.Tobin\ Q_{-i,t}$ (that is, the first-difference of the variable $Tobin\ Q_{-i,t}$) are likewise positive and statistically significant in this case, validating the results obtained with the basic model.

While the regression above just supports previous findings in the literature, what follows is novel.

To account for the influence of product portfolio similarity (*Result 1*), in all of the Columns (1) to (4) of Table 3, I utilized Hoberg and Phillips' similarity coefficient.

I calculated the median value of the similarity coefficient for each 4D NAICS and year. Then I created a dummy variable called "Dummy divers". If the similarity coefficient between firm i and firm -i (belongs to the same 4D NAICS) is higher than the median in that 4D NAICS and year, this variable equals 1. Finally, I interact the Tobin's Q of firm -i with "Dummy divers" and I build a new variable by squaring this last coefficient. As a result, while estimating the sensitivity of the firm i's investment on firm -i's Q, I additionally consider the marginal effect of product portfolio similarity. The findings I obtained are shown in Table 3.

It's interesting is to examine how products portfolio diversification affects the marginal effect of firm B's stock price on firm A's investment. That is, using the regression equation N.2. from section 3.2, $E(\frac{\delta I_i}{\delta Q_{-i}}) = \eta_0 + \eta_1 \lambda_{i,-i,t} + 2\eta_2 Q_{-i,t-1} \times$

$\lambda_{i,-i,t}^2$. When the dummy ($\lambda=1$) equals “1”²⁵ the equation becomes: $E(\frac{\delta I_i}{\delta Q_{-i}})$
 $= \eta_0 + \eta_1 + 2\eta_2 Q_{-i,t-1}$.

Then, when *Dummy divers* is 0 (that is $\lambda=0$) the marginal effect becomes: $E(\frac{\delta I_i}{\delta Q_{-i}}) = \eta_0$.

Table 3 – Baseline specification (Results 1 and 2)

This table reports the estimates obtained using a fixed effects model regression of the investment ratio of firm *i* at time *t*, on product portfolio diversification between firm *i* and *-i*, and controls. I used two different dependent variables in these specifications: In Column (1), I used the ratio of firm *i*'s Capex in year *t* to its lagged total assets, in Column (2), I used the ratio of firm *i*'s Capex in year *t* to its lagged book value PP&E. *Tobin Q* is the proxy of firm *i* and *-i*'s stock prices computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm *i* at time *t*. *Size* is the natural logarithm of total assets of firm *i* at time *t*. *Leverage* is the ratio of total debt on total assets of firm *i* at time *t*. *Manager inform.* is the proxy for the firm *i*'s manager informativeness, computed as the average one-month return in year *t* of the firm *i*'s insiders. *Dummy divers.* is a dummy variable that equals 1 if the measure of firms *i* and *-i* product portfolio homogeneity exceeds the 4D NAICS median. In Columns (3) and (4) I used a first-difference fixed effects model to address endogeneity issues. In Columns (5) and (6) I empirically tested *Result 2*, which is the effect of the quality of managerial information on the covariance between firm *i*'s investments and firm *-i*'s stock prices. All control variables are winsorized at both 1% and 99% and standardized. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at the firm level. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variables	Capex Ratio _{i,t} (1)	Capex /PP&E _{i,t} (2)	D.Capex Ratio _{i,t} (3)	D.Capex /PP&E _{i,t} (4)	Capex Ratio _{i,t} (5)	Capex /PP&E _{i,t} (6)
<i>Dummy divers.</i>	-0.173* (0.103)	-1.135*** (0.324)		-0.134 (0.262)		
<i>Tobin Q_{-i,t-1}</i>	0.206*** (0.048)	0.409* (0.232)			0.005 (0.0271)	0.325** (0.138)
<i>Dummy divers. x Tobin Q_{-i,t-1}</i>	0.372*** (0.099)	1.584*** (0.381)				
<i>(Dummy divers. x Tobin Q_{-i,t-1})²</i>	-0.078*** (0.018)	-0.295*** (0.080)				
<i>Manager inform. _{i,t-1} x Tobin Q_{-i,t-1}</i>					-0.0005** (0.0002)	-0.0050*** (0.001)
<i>Manager inform. _{i,t-1}</i>					0.003*** (0.0005)	0.0186*** (0.003)
<i>D.Dummy divers. x Tobin Q_{-i,t-1}</i>			0.195* (0.109)	0.579** (0.248)		
<i>D.(Dummy divers. x Tobin Q_{-i,t-1})²</i>			-0.058*** (0.019)	-0.114* (0.060)		
<i>Tobin Q_{i,t-1}</i>	0.406*** (0.039)	3.014*** (0.173)			0.716*** (0.0360)	3.481*** (0.161)

²⁵ i.e., when the firm *i* and *-i* had a similarity's coefficient greater than the average in that year of the firms belong to the same firm *i*'s NAICS, thus $\lambda=1$;

<i>Capex Ratio</i> _{-i,t-1}	0.387*** (0.070)				0.472*** (0.048)	
<i>Leverage</i> _{i,t-1}	-0.637*** (0.040)	-2.121*** (0.105)			-0.489*** (0.030)	-2.057*** (0.121)
<i>Leverage</i> _{-i,t-1}	-0.092** (0.043)	-0.105 (0.150)			-0.014 (0.032)	-0.110 (0.144)
<i>Size</i> _{i,t-1}	-1.177*** (0.174)	6.810*** (0.739)			-0.715*** (0.114)	6.484*** (0.684)
<i>Size</i> _{-i,t-1}	0.200 (0.153)	0.684 (0.520)			0.224** (0.106)	0.258 (0.478)
<i>Capex/PP&E</i> _{-i,t-1}		0.167 (0.103)				0.190** (0.094)
<i>D.Dummy divers.</i>			-0.0366 (0.115)			
<i>D.Tobin Q</i> _{-i,t-1}			0.200*** (0.056)	0.558*** (0.208)		
<i>D.Tobin Q</i> _{i,t-1}			-0.334*** (0.065)	1.219*** (0.203)		
<i>D.Capex Ratio</i> _{-i,t-1}			0.118 (0.086)			
<i>D.Leverage</i> _{i,t-1}			-0.594*** (0.049)			
<i>D.Leverage</i> _{-i,t-1}			-0.046 (0.049)			
<i>D.Size</i> _{i,t-1}			-5.778*** (0.305)	4.540*** (1.057)		
<i>D.Size</i> _{-i,t-1}			-0.008 (0.254)	2.896*** (0.832)		
<i>D.Capex/PP&E</i> _{-i,t-1}				0.052 (0.102)		
<i>D.Leverage</i> _{i,t-1}				-0.855*** (0.168)		
<i>D.Leverage</i> _{-i,t-1}				-0.221 (0.188)		
<i>Constant</i>	8.339*** (0.665)	-5.156** (2.516)	-1.250 (0.903)	-8.034*** (2.632)	6.347*** (0.421)	-4.336* (2.297)
Observations	35,564	35,479	27,092	27,018	46,542	35,493
R-squared	0.077	0.081	0.145	0.154	0.099	0.107
Number of id_couple	5,943	5,940	-	-	6,112	5,943
Firm Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Firm Pair	Firm Pair	Firm Pair	Firm Pair	Firm Pair	Firm Pair

Given that the coefficients $\eta_1=0.372$ and $\eta_2=-0.078$ in my estimates, and assuming for simplicity that $Q_{-i,t-1}$ is equal to its mean, 2.183²⁶, I can conclude that, all else being equal, a one standard deviation increase in Tobin's Q of peers with more similar products portfolio implies an increase of more than 0,24 percentage points of investments ratio compared to the same change in less similar peers. Additionally, with a t-statistic of 3,74 (η_1) and -4,40 (η_2) all the coefficients are highly significant.

²⁶ see Table 1;

Furthermore, the estimation findings show that this impact has a diminishing marginal return on the increase in the stock prices of peers. That is, if $Q_{-i,t-1}$ reaches extremely high levels, the marginal effect of a rise in Tobin's Q of peers with more similar products shifts. In reality, a sharp increase in the stock prices of peers is followed by increased market volume. If the degree of product portfolio homogeneity between firms A and B is high, speculators will trade on both firm A's and firm B's stock prices. As a result, firm A's stock price becomes very informative for firm A's manager. The effect of an increase of informed speculators on the covariance between firm A's investment and firm B's stock price is ambiguous in my theoretical model. Specifically, only if the product between δ and ρ is large enough ($\delta\rho > \delta\rho'$), will the rise in both firm B's and firm A's informed speculators cause an increase in the information of firm B's stock price bigger than that of firm A, leading the manager of company A to give stock B a higher weight. Conversely, the covariance drops because the stock price of firm A becomes more informative for firm A's manager than the stock price of firm B. Therefore, this result is consistent with what I find in my theoretical model. An alternate and more natural explanation is as follows: when the peers' stock prices are excessively high, the manager will rely less on them since he believes the price increase is due to a temporary overvaluation of the stock rather than an improvement in the industry's market conditions.

In Column (2), I utilized the ratio of the firm i's Capex in year t to its book value property, plant, and equipment at time t as the dependent variable, validating the results reported in Column (1).

Furthermore, in Columns (3) and (4) I used a first-difference fixed-effects model to estimate the same regressions in Columns (1) and (2).

The first-differenced estimator is a method for dealing with the problem of omitted variables when employing panel data.

Therefore, using this method I try to fix my model to potential endogeneity issues. I found positive and statistically significant coefficients associated with the variable $D.Dummy\ divers. \times Tobin\ Q_{-i,t-1}$ and negative and statistically significant coefficients associated with the variable $D.(Dummy\ divers. \times Tobin\ Q_{-i,t-1})^2$.

Lastly, in the final two columns of Table 3, I address *Result 2* empirically.

According to *Result 2*, the covariance between a firm's investment (I_A) and the stock price of its peers (p_B) diminishes with the quality of managerial information (γ). To test this finding, I established an interaction variable between the proxy of the firm i's manager informativeness ($Manager\ inform_{i,t-1}$), calculated as the average return of firm i's insider trading activity in year t, and the proxy of peers' stock price ($Tobin\ Q_{i,t-1}$).

To compute the variables $Manager\ inform_{i,t-1}$ I downloaded from Eikon Refinitiv all the insider transactions of the top executives²⁷ for each firm for a given year. Then, I computed their annual average of the one month buy-and-hold returns. The idea is that the more profit insider traders make, the more confidential information they have.

If *Result 2* is correct, the coefficient associated with the interaction variable ($Manager\ inform_{i,t-1} \times Tobin\ Q_{i,t-1}$) is expected to be negative. In fact, both in Columns (5) and (6), despite using two different dependent variables, we found a negative and statistically significant coefficient associated with the interaction variable $Manager\ inform_{i,t-1} \times Tobin\ Q_{i,t-1}$.

These results are robust using standard errors robust for heteroskedasticity and clustered at firm pair level.

This conclusion validates the theoretically found one and reflects the fact that if the manager of the firm i has a lot of private information, he will rely less on the peers' stock prices in her firm's investment decision.

To conclude, in Table 4 I empirically tested the *Results 3* and *4*, that is the effects of product portfolio diversification and firm i's manager informativeness on the covariance between the investment of a firm (I_A) and its own stock price (p_A).

In Columns (1) and (2), I tested *Result 3*, which states that, in the learning scenario, an increase in product portfolio homogeneity (δ) does not necessarily imply a reduction in the covariance between firm i's investment and its own stock price; rather, this will occur only if the manager of the firm A has a lower quality of internal information (γ). To do so, I split the sample into two sub-samples: one in which the informativeness of the firm i's manager is higher than that of its peers, and one in which the informativeness of the firm i's manager is lower than that of its peers.

²⁷ that is, CEO, CFO, COO, President, and Chairman of the Board;

Table 4 – Results 3 and 4

This table reports the estimates obtained using a fixed effects model regression of the investment ratio of firm i at time t , on firm i 's stock price and controls. I used a unique dependent variables in these specifications, the ratio of firm i 's Capex in year t to its lagged total assets. *Tobin Q* is the proxy of firm i and $-i$'s stock prices computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . *Size* is the natural logarithm of total assets of firm i at time t . *Leverage* is the ratio of total debt on total assets of firm i at time t . *Similarity* is the Hoberg and Phillips' (2016) measure of product portfolio homogeneity. *Manager inform.* is the proxy for the firm i 's manager informativeness, computed as the returns in year t of the firm i 's insiders. In Column (1) I ran the model on a subsample of firms with managers who are more informed than that of their peers at 4D NAICS level. The higher the Similarity the more similar the product portfolios of firms i and $-i$ are. In Column (2) I ran the model on a subsample of firms with managers who are less informed than that of their peers at 4D NAICS level. In Columns (3) and (4) I ran the model dividing the sample into two subsamples according to the market information in year t (Column (3) HIGH market information and Column (4) LOW market information) to study the impact of the managerial information on the covariance between firm i 's investment and its stock price. All control variables are winsorized at both 1% and 99% and standardized. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at the firm level. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variable	Capex Ratio $_{i,t}$			
	Manager inform. HIGH	Manager inform. LOW	Market information HIGH	Market information LOW
<i>Manager inform$_{i,t-1}$</i>			-3.26e-05 (5.61e-05)	0.004*** (0.001)
<i>Tobin Q$_{i,t-1}$</i>	0.817*** (0.082)	0.679*** (0.073)	0.698*** (0.086)	0.794*** (0.041)
<i>Similarity</i>	5.728** (2.409)	5.379*** (1.777)		
<i>Similarity x Tobin Q$_{i,t-1}$</i>	-1.833** (0.871)	2.396** (0.980)		
<i>Manager inform$_{i,t-1}$ x Tobin Q$_{i,t-1}$</i>			8.43e-05** (4.18e-05)	-0.001** (0.0002)
<i>Tobin Q$_{-i,t-1}$</i>	-0.041 (0.042)	-0.044 (0.036)	0.059 (0.089)	0.031 (0.032)
<i>Capex Ratio$_{-i,t-1}$</i>	0.602*** (0.096)	0.620*** (0.089)	0.429* (0.258)	0.608*** (0.072)
<i>Leverage$_{i,t-1}$</i>	-0.297*** (0.029)	-0.346*** (0.036)	-0.809*** (0.128)	-0.544*** (0.034)
<i>Leverage$_{-i,t-1}$</i>	-0.048 (0.055)	-0.038 (0.044)	-0.114 (0.108)	-0.029 (0.038)
<i>Size$_{i,t-1}$</i>	1.825*** (0.181)	0.749*** (0.133)	-0.594 (0.388)	-1.110*** (0.160)
<i>Size$_{-i,t-1}$</i>	-0.337* (0.203)	0.0430 (0.146)	-0.147 (0.458)	0.259** (0.124)
<i>Constant</i>	0.567 (0.692)	2.521*** (0.597)	7.612*** (1.829)	7.408*** (0.543)
Observations	23,030	23,488	5,960	40,582
R-squared	0.099	0.095	0.091	0.087
Number of id_couple	5,145	5,199	3,108	6,106
Firm Pair FE	Yes	Yes	Yes	Yes
S.E. Cluster	Firm Pair	Firm Pair	Firm Pair	Firm Pair

Then, as a proxy for product portfolio homogeneity, I utilized the Hoberg and Phillips (2016) coefficient (*Similarity*), which ranges from 0% to 100% based on the number of words shared by two paired firms in their product description. As predicted by the theoretical model, I found a negative and statistically significant coefficient associated with the interaction variable $Manager\ inform_{i,t-1} \times Tobin\ Q_{i,t-1}$ in the subsample where firm i's manager's informativeness is high, and a positive and statistically significant coefficient in the subsample where the informativeness of firm i's manager is low. That is, when the initial informativeness of the firm i's manager is low, the covariance between the firm i's investment and its own stock price increases with the degree of product portfolio similarity, and vice versa.

Finally, in the final two columns, I provide empirical support for *Result 4*. It claims that if the market has a large amount of information, an increase in the quality of management internal information leads to a higher covariance between the firm i's investment and its own stock price. The informativeness of firm i's stock price, the informativeness of firm -i's stock price, and the degree of product portfolio homogeneity provide the level of market information. This is because, according to the order flow in Section 2.1, the greater the degree of product portfolio similarity (δ), the more the informed speculator on firm -i that will invest in firm i; hence, the more will be market information.

Following Roll (1988), Chen et al. (2007), and Foucault and Fresard (2014) I measure the informativeness of a firm stock price by its firm-specific return variation (or price non-synchronicity), defined as $\ln((1-R^2_{i,t})/R^2_{i,t})$ where the $R^2_{i,t}$ is that from the regression in year t of firm i's weekly returns on market returns and the peers' value-weighted portfolio returns. The idea is that the more a firm's stock price is based on firm-specific information, the less correlated its return is with that of its peers and the market.

Moreover, using the same approach as to test *Result 3*, I divided the sample into two sub-samples: one high market information, and one with low market information.

That is, if the degree of product portfolio homogeneity between firms i and -i is greater than the median in the same 4D-NAICS and year, and both firm i's and -i's specific

return variations are greater than the median in the same 4D-NAICS and year, the paired firm i and $-i$ will belong to the first subsample in which market information is high.

As shown in Columns (3) and (4), when market information is high, an increase in the manager informativeness of company I results in a larger covariance between firm i 's investment and its own stock price (i.e., the coefficient associated with the interaction variable $Manager\ inform_{i,t-1} \times Tobin\ Q_{i,t-1}$ is positive and statistically significant). When market information is scarce, vice versa (the coefficient of the interaction variable $Manager\ inform_{i,t-1} \times Tobin\ Q_{i,t-1}$ is negative and statistically significant).

These findings support the theoretically derived results in the learning scenario.

Based on these findings, I can infer five major conclusions: first, I validate the findings of Foucault and Fresard (2014) by obtaining consistent outcomes utilizing a different period of data. As a result, managers gain more information to make investment decisions by studying their peers' stock prices on the market. This empirical observation is well-documented in the literature.

Second, my results show that managers pay more attention to and learn more from their peers' stock prices who have more similar product portfolios. This is also consistent with the growing trend of firms investing substantial sums of money in R&D in order to diversify their product range and preserve their investment strategy.

Third, I suggest this influence is decreasing on the firm's manager informativeness, since when she has a lot of information, she would rely less on peers' stock prices to make investment decisions for her firm.

To conclude, a high homogeneity degree products portfolio doesn't always imply a decrease in the covariance between firm i 's investment and its own stock price. In fact, this will occur only if the manager of the firm A has a lower quality of internal information (γ) or there is a lot of information in the market.

4. Conclusions

In recent years, there has been a growing body of research focused on the impact of secondary financial markets on the investment decisions of company managers. Ozoguz and Rebello (2013) were the first to identify the "learning from peers' stock

price” mechanism demonstrating that an increase in the average of peer firms’ stock prices is associated with a statistically significant increase in the firm’s capital expenditure.

This literature has since been expanded upon by Foucault and Fresard (2014), Huang and Zeng (2015), Dessaint et al., (2019), and Yan (2020). Following this strand of the literature, my paper aims to investigate if and to what extent product diversification can mitigate the informational power of stock prices available to competitors, and the information that managers can obtain by observing changes in stock prices.

Based on the theoretical framework developed by Foucault and Fresard (2014), I developed a model that has four main findings that are unique to the learning scenario. Firstly, I found that the informativeness of peers’ stock prices increases with the degree of product portfolio similarity (δ in the model). As a result, the covariance between a firm and its peer’s stock price increases with the degree of product portfolio homogeneity (δ) between them.

Secondly, I found that this influence is decreasing on the firm’s manager informativeness.

Lastly, this effect does not necessarily imply a reduction in the covariance between I_A and p_A . Instead, this only occurs if either firm A’s manager has a lower quality of internal information (γ) or there is a lot of information in the market. My empirical findings confirm these theoretical results.

Specifically, I discovered that managers pay more attention and learn more from observing the stock prices of their more similar products portfolio peers.

I found that a one standard deviation increase in Tobin’s Q of peers with more similar products portfolio implies an increase of about 0,24 percentage points of investments ratio compared to the same change in less similar peers. This may seem like a small percentage, but in economic terms, it represents an annual increase of more than €18 million per firm and more than \$13 billion in total capex in our sample. This effect is statistically and economically significant and shows that managers are more affected by the change in the price of their more similar products portfolio’s peers, i.e., the “learning from peers’ stock mechanism” is stronger in that case.

Moreover, I found that this influence is decreasing on the firm's manager's informativeness, given that when she has a lot of information, she will rely less on the stock price in the market.

In conclusion, my empirical results confirm that a high degree of homogeneity in a firm's products portfolio leads to a decrease in the covariance between the firm's investment and its own stock price if the manager has lower-quality internal information (γ) or if there is a significant amount of information available in the market.

These last four results are new and extend the results achieved by Focault and Fresard (2014) by highlighting the role to product diversification on the “learning from peers’ stock price” mechanism.

Furthermore, these results suggest that product portfolio diversification can serve as a useful tool for managers to defend against strategic imitation by their peers and preserve the competitive advantage of their company.

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Chapter 3: Do market feedbacks affect corporate dividend policy?

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Abstract

Stock prices, aggregating information from a large number of different investors in the financial markets, allowing actual decision makers to infer knowledge useful to take corporate dividend policy decisions. In this paper, by developing a theoretical model in which managers learn from their peers' stock prices, I investigate the impact of such learning on firms' dividend policy decisions. The empirical analysis is conducted using a dataset of 629 US firms between 2002 and 2019. The findings reveal that, uniquely in the managerial learning scenario, the probability of distributing dividends for a company whose manager observes the market's feedback is lower than for a company whose manager does not learn from the market. Additionally, the covariance between the dividend policies of two peers' companies is greater in the managerial learning scenario than in the case of no learning. Further, the covariance increases with the stock price informativeness of firm B (π_B), while it decreases with the stock price informativeness of firm A (π_A). These findings are uniquely predicted by a theoretical model in which managers learn information from market feedback on their peers' dividend policy decisions.

Keywords: payout policy, real decision makers, learning from peers' stock prices, corporate decisions, price efficiency, feedback effect, managerial learning;

1. Introduction

Starting with Hayek's claim in 1945 that prices are a helpful source of information, a growing literature on the impact of stock prices and their fluctuations on real decision-makers developed.

Stock prices, in fact, aggregate information from a large number of different investors in financial markets, giving decision-makers access to knowledge that would otherwise be inaccessible, thereby improving their decision-making ability.

Bond and Goldstein (2015), for example, developed a model of information aggregation in financial markets in which government utilizes information embedded in prices to make an intervention decision.

Even though this information affects a large number of real decision-makers (ranging from regulators and policymakers to credit rating agencies and speculators¹), one area of research that has attracted considerable attention is the effects of stock prices on managers' corporate decisions.

There are several cases in which managers are affected by the stock prices of their own companies or peers. A consolidated literature on this topic began with Tobin (1969) and continued with Fama (1981), Barro (1990), Morck et al. (1990), Blanchard, Rhee, and Summers (1993), and Allen (1993), which shown that stock prices have a significant influence on firms' internal investment decisions by affecting managers' decisions. These studies have spurred the development of several lines of research: for instance, managers' decisions are affected by the changes in stock prices and by their informativeness during M&A transactions², by the stock prices' informativeness of cross-listing companies³, and by both past returns and informativeness of stocks when they are involved on IPO decisions⁴.

In recent years, the focus moved towards how managers learn from their own stock prices when determining firms' investment decisions⁵, as well as how the information contained in peers' stock prices impacts managers' decisions through the so-called "managerial learning"⁶. The majority of works in this last line of study have been focused on how managerial learning affects firms' investment policy decisions.

¹ To explore these parts of literature see: Bernanke and Woodford (1997), Feldman and Lavinian (2001), Burton and Seale (2005), Hart and Zingales (2011), Bond and Goldstein (2015), Boleslavsky et al. (2017), Siemroth (2019), Baeriswyl et al. (2020), Siemroth (2021) for the effects on regulators, policy-makers and credit rating agencies; Goldstein and Guembel (2008), Edmans et al. (2015), Boehmer et al. (2013), Grullon et al. (2015), De Angelis et al. (2017), Nezafat et al. (2020) for the effects on short-selling and arbitrageurs; Bond and Eraslan (2010), Goldstein et al. (2011a-b), Edmans et al. (2011), Goldman and Strobl (2013), Albuquerque and Schroth (2015), Chang et al. (2017), Dou et al. (2018), Chung et al. (2020) for the effects on investors, speculators and bondholders;

² see Luo (2005), Bond et al. (2010), Ouyang and Szewczyk (2016), Bade (2017), Chira et al. (2017), Anderson et al. (2017) and Ouyang et al. (2018);

³ see Foucault and Gehrig (2008), Foucault and Fresard (2014), Kusnadi (2015), Abdallah and Abdallah (2017) and (2019);

⁴ see Subrahmanyam and Titman (1999), Van Bommel and Vermaelen (2003), Chen and Guo (2010), Rossetto (2013), Premti and Madura (2013), Vong and Trigueiros (2017), Huang et al. (2019), Gao et al. (2020);

⁵ see Chen et al. (2007), Campello and Graham (2008), Goldstein and Guembel (2008), Bakke and White (2010), Fresard (2010), Edman et al. (2015), Dow et al. (2017), Mama (2017), Pedraza (2019), Jayaraman and Wu (2020), Xiao (2020), Da Silva (2021)

⁶ see Ozoguz and Rebello (2013), Foucault and Fresard (2014), Huang and Zeng (2015), Mama (2017), Dessaint et al. (2019), Lee (2020);

On the contrary, the impact of the learning mechanism on dividend policy decisions has been relatively limited.

However, it is common to observe that companies belonging to the same industry make similar decisions about their dividend policies. For example, Apple announced to restart to pay dividends in March 2012, after not paying dividends for more than 15 years, and less than a year later its' main peer, Cisco Systems, began paying dividends in April 2011. In that case, the market reacted very positively at Cisco System's management decision: the stock price increased by more than 3% in the following three market sessions and after two weeks the stock increased by more than 7% despite the ex-dividend date⁷.

Actually, De Cesari Huang and Meier (2015) have shown that managers exploit private information conveyed by their firms' stock returns when deciding the dividend policies of their companies. As such, managers "listen the markets", given that corporate events and changes in corporate policies are sensitive to market reactions. More recently, Adhikari and Agrawal (2018) demonstrated that firms' payout policies are significantly influenced by the policies of their industry peers, consistent with the rivalry-based theory.

However, there has been little attention paid to whether and why the learning mechanism affects the dividend policy decision-making process of firms' managers. This paper aims to fill this gap by developing a theoretical model in which two peer firms consecutively determine their dividend policy, thereby triggering the learning mechanism. Between the dividend policy decisions of the two firms, the market determines stock prices by providing feedback on the dividend policy decision of the firm that determines its policy first. In order to complete her information set, the manager of the second firm in the sequence would analyze the market response (feedback) on the competitor's dividend policy decision and thus gain information learning from market prices⁸.

⁷ Likewise, after the announcement, Apple stock price increase of about 10% in the next two weeks;

⁸ the stock prices of the two firms will be determined from the market at the same time. As a result, the manager of the firm that sets its dividend policy second may also examine the stock price of its own firm when deciding her dividend payout policy;

The theoretical findings of the model are the following: i) when the conditions of the managerial learning are satisfied, the probability of distributing dividends for a company whose manager observes the market's feedback is lower than for a company whose manager doesn't learn from the market; ii) uniquely in the managerial learning scenario, the covariance between the dividend policies of the two peers' companies increases with the stock price informativeness of firm B (π_B). On the other hand, it decreases with the stock price informativeness of firm A (π_A), while the effect of an increase in firm A's manager informativeness (γ_A) is ambiguous; iii) the covariance between the dividend policies of the two competing firms is higher in the managerial learning scenario than in the absence of learning.

To test the theoretical hypothesis, I used a dataset of more than 60.000 observations from 629 US firms from 2002 to 2019 from Compustat. I empirically address the points i) to iii) using as baseline specification a fixed effects model with a within estimator.

Furthermore, to address the endogeneity issue that arose from the empirical examination of point iii) I used an IV approach according to Anderson and Hsiao, (1981). Following the two authors, I use two instruments to instrument our endogenous variables⁹, namely the two period-lagged interested variables and the first difference of the two period-lagged interested variables.

My findings suggest that the activation of the learning mechanism results in a decrease of approximately 0,9% in the a priori probability of firm i of distributing dividends when there is one standard deviation in the variable $Learn_i$ ¹⁰.

Additionally, in the presence of all the conditions required for learning, the covariance between the two competing firms' dividend policy increases by approximately 34.6% compared to the no-learning scenario. These results are statistically significant and robust across various specifications, and have important economic implications.

The model has several economic implications. Firstly, despite the dividend policies' decisions following a complex logic since it involves capital structure, investment, and

⁹ the two endogenous variables are the proxy of the firm B's dividend policy, that is the dividend policy of the competitor firm, and the interaction variable between the proxy of the firm B's dividend policy and the $Learn_i$ dummy variable;

¹⁰ i.e, the dummy variable which is equal to 1 when the managerial learning's conditions are met. For major details see Section 4.2.1;

strategical decisions¹¹, the learning mechanism influences the managers' choices about dividend policy by increasing the covariance with that of their peers' by reducing the randomness with which uninformed managers determine it. In fact, the observation of competitors' choices and the variation in their stock prices provides managers with a set of information that they could not have obtained otherwise, thus improving the efficiency with which managers will determine the payout policy of their firm. Secondly, according to Dow and Gorton (1997) and Chen et al. (2007), managers can gather a lot of private information about the demand for their firm's products, investment opportunities, and the competitive environment in which their firm operates from stock prices formed by traders' activities.

This implies that when peers companies make decisions that receive positive market reactions, managers tend to adopt similar strategies concerning them, rising the covariance between dividend policies. On the other hand, when such learning is absent, there is a lower covariance between these dividend policies¹². Interestingly and in a novel manner, my findings appear to reveal a mechanism of a "benchmark to peers' behavior" that influences managers concerning the dividend policy decisions of their firms, which is achieved through the observation of market prices.

This paper contributes to two lines of research. Firstly, it examines the role of price informativity in firms' payout policy decisions by learning from peers' stock prices. Specifically, it is the first paper to investigate this impact by developing a theoretical model in which competing firms sequentially determine their dividend policy.

Secondly, it contributes to the body of knowledge on the determinants that affect firms' payout policy decisions. While previous research on the topic has focused on traditional explanations such as agency, signaling, and taxes, this study suggests that the informativeness of market pricing could be a new factor guiding managers' dividend payout policy decisions, as highlighted in the survey conducted by Farre-Mensa, Michaely, and Schmalz (2014).

¹¹ see Baker and Powell (2000) for a survey;

¹² The results seem to highlight that also in the dividend policy decision could exist a benchmark to peers' behavior as also stated by J.P. Morgan in the 2011 Guide to Dividend policy trends and best practices 'we believe that a best-in-class dividend policy should be based on the five CLIMB dimensions: Capital planning, Long-term sustainability, Investor preferences, Materiality and Benchmarking to peers'".

The paper proceeds as follows. In the next section, I develop the theoretical model. Section 3 derives the testable implications. In Section 4 I describe the empirical methodology. In Section 5 I empirically test the theoretical predictions. Section 6 concludes by resuming the main results.

2. Theoretical framework

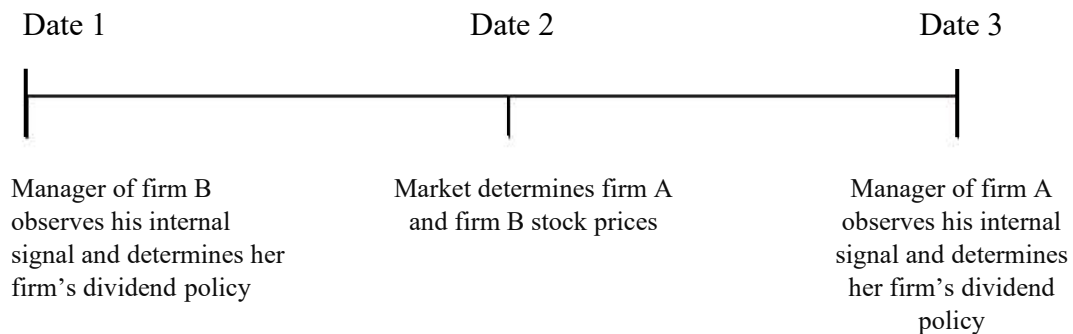
2.1 Theoretical model

To demonstrate how market feedback affects managers' dividend policy decisions, I developed a simulation with two competing companies, A and B. Following Kyle (1985) and Foucault and Fresard (2014), the product demands of the two firms can be more or less correlated based on a common factor (ρ), that is

$$\Pr(d_A=H \mid d_B=H) = \Pr(d_B=H \mid d_A=H) = \rho$$

Dividend policy decisions are made consecutive by the two companies (see Figure 1). The following is the model's timeline: first, the manager of firm B determines his own firm dividend policy based on the internal signal she receives about her firm's future demand. Second, the prices of stocks A and B are determined by the market. Third, the manager of the firm A determines her own firm's dividend policy based on both her internal signal and market prices. Finally, the two firms' product market demands are realized.

Figure 1 – Timeline of the model



2.2 Stage 1: Firm B's dividend policy decision

Initially, firm B's manager determines its dividend policy (D_B) based on the internal signal she observes about her firm's future demand (S_B).

The demand could be High (H), Low (L) or unobserved ($\emptyset$), that is $S_B = \{H, L, \emptyset\}$.

When $d_B=j$ ($d_A=j$), then $s_B=j$ ($s_A=j$) with probability γ or $s_B=\emptyset$ (no signal) ($s_A=\emptyset$) with probability $(1-\gamma)$. Namely, γ_j with $j = \{A, B\}$ represents the quality of “direct managerial information”.

Following these assumptions, she pays dividends ($D_B=D_B^H$) if her internal signal about her firm's future demand is strong ($S_B=H$); she does not pay dividends if her internal signal is weak ($S_B=L$); and she pays dividends with a probability of $\frac{1}{2}$ if she receives no internal signal ($S_B=\emptyset$) about her firm's future demand.

Therefore, the probability to distribute dividends for firm B is equal to:

$$\begin{aligned} \Pr(D_B=D_B^H) &= \Pr(D_B=D_B^H|S_B=H)\Pr(S_B=H) + \Pr(D_B=D_B^H|S_B=\emptyset)\Pr(S_B=\emptyset) + \\ &\Pr(D_B=D_B^H|S_B=L)\Pr(S_B=L) = \frac{1}{2}. \end{aligned}$$

Similarly, the $\Pr(D_B=\emptyset) = \frac{1}{2}$.

2.3 Stage 2: Price formation process on the market

In the second stage, the market determines the price of stocks A and B. Following Foucault and Fresard (2014), there are three types of investors in the stock market: a) a continuum of risk-neutral speculators, b) liquidity traders with an aggregate demand z_j , uniformly distributed over $[-1,1]$, and c) risk-neutral dealers. Speculators receive a signal $s_{ij} = \{H, L, \emptyset\}$. However, only a fraction π_j of speculators receives a perfect signal, i.e., $s_{ij}=d_j$, about the future demand for the product firm $j = \{A, B\}$. The remaining fraction of speculators, $1 - \pi_j$, observe no signal about the future demand of the firm j ($s_{ij}=\emptyset$).

The price formation process of the two peers' stock prices differs: the price of stock B is determined by speculators' reaction to the choice of firm B's manager after they observe the signal; the price of stock A, on the other hand, is determined solely speculators' forecast of firm A's future demand.

In the case of firm B, the market reacts to the manager's decision determining firm B's stock price in the following ways:

After receiving her signal about firm B's future demand, a speculator can buy one share of the stock B if:

- the speculators receive a positive signal about firm B's future demand, and the company's manager decides to distribute dividends;
- the speculators receive a negative signal about firm B's future demand, and the company's manager decides not to pay dividends¹³;

In contrast, a speculator can decide to sell one share of stock B if and only if the following conditions are met:

- the speculators receive a negative signal about firm B's future demand, and the company's manager decides to pay dividends;
- the speculators receive a positive signal about firm B's future demand, and the company's manager decides not to pay dividends;

The logic is as follows: if the speculator receives a positive signal about firm B's future demand and the manager decides to distribute dividends, or if the speculator receives a negative signal and the manager decides not to distribute, the market responds positively by deciding to buy a share of stock B because it values the manager's choice and her ability to obtain information and it is confident that she will be able to make good decisions for the firm also in the future¹⁴.

Furthermore, if the market expects firm B's future demand to be strong, a commitment through dividend distribution will be valued.

Instead, the market reacts negatively in the other two cases: in the first case (negative future demand and dividend distribution by firm B's manager), the company's financial sustainability will be compromised (if the manager commits to distribute dividends

¹³ For simplicity of understanding, in this case, I assumed that the company does not pay dividends. In reality, dividend policies are often consistent over time, so it is uncommon for a company with a regular dividend policy to stop the distribution. This is due to the market's negative reaction. As a result, in our framework, non-payment of dividends can be easily interpreted as a reduction in dividends distribution rather than a cessation of them;

¹⁴ This is in line with the contracting hypothesis (Xu (2021)) which states that stock price reflect information about the quality of managers' decisions.

and the future demand is negative, the manager will be forced to take more debt to keep her dividend policy constant or to stop the distribution of dividends).

In the second scenario (high future demand and firm B's manager refusing to distribute dividends), the manager will fail to maximize shareholder value, and the firm will lose its appeal to higher-return peers. So, the market prices are determined by speculators' trades.

Let f_j be the order flow for stock j , i.e. the sum of speculators' and liquidity traders' net demand:

$$f_j = z_j + x_j$$

$$\text{where } x_j = \int_0^1 x_j(s_j) di \text{ and } x_{-j} = \int_0^1 x_{-j}(s_{-j}) di.$$

The information in the order flow determines the price of stock j : dealers match the demand for stock j at a price that brings the order flow into equilibrium.

As a result, as stated also by Foucault and Fresard (2014), the stock price of firm B, $p_B^*(f_B)$, is an increasing step function of investors' net demand for this stock, f_B . Thus, $p_B^*(f_B) = \theta_B^H$ if $f_B > 1 - \pi_B$, $p_B^*(f_B) = \theta_B^L$ if $f_B < -1 + \pi_B$, $E(\theta_B)$ if $-1 + \pi_B < f_B < 1 - \pi_B$.

In fact, a speculator i purchases stock B when she is informed that demand for firm B's product is high and the firm B's manager has decided to distribute dividends, or when demand for firm B's product is low and firm B's manager has decided not to distribute dividends ($x_{iB}^*(H) = +1$). The speculator sells it in the other two cases described above ($x_{iB}^*(L) = -1$).

The interpretation is as follows: if the investor's net demand is relatively strong, i.e. $f_B > 1 - \pi_B$, dealers conclude that speculators received a positive signal regarding the choice of firm B's manager. As a result, the stock price of B is high (θ_B^H).

Similarly, but using the opposite logic, if investor's net demand is relatively low, i.e. $f_B < -1 + \pi_B$, dealers infer that speculators received negative signals about the choice of firm B's manager and the price of stock B is low (θ_B^L). For the intermediate realizations, dealers cannot infer the signals received by the speculators and the investors' net demand ($-1 + \pi_B < f_B < 1 - \pi_B$) is not informative. Thus, for these realizations, the price of stock B is just equal to the unconditional expected value.

About the stock price of firm A, on the other hand, a speculator i buys stock A when she knows that demand for firm A's product is high ($x_{iA}^*(H) = +1$), she sells it when she

knows that demand for firm A's product is low ($x_{iA}^*(L)=-1$), and she does not trade otherwise ($x_{iA}^*(\emptyset)=0$).

The stock price of firm A, $p_A^*(f_B)$, is an increasing step function of her stock's net demand from investors, f_A . Thus, $p_A^*(f_A)=\theta_A^H$ if $f_A>1-\pi_A$, $p_A^*(f_A)=\theta_A^L$ if $f_A<-1+\pi_A$, and $E(\theta_A)$ if $-1+\pi_A < f_A < 1-\pi_A$.

2.4 Stage 3: Firm A's dividend policy decision

Following firm B's decision, and aftermarket prices and information feedback from them have been established, the manager of the firm A determines his own firm's dividend policy.

As stated above, the manager of firm A observes realized stock prices and, like the manager of firm B, notices a signal, $S_A = \{H, L, \emptyset\}$, about his firm's future demand.

I developed three scenarios: the manager of firm A can decide his own firm dividend policy based solely on his internal signal¹⁵ ("No Learning Case"), solely on his internal signal and his own stock price ("Narrow Learning Case"), or on his internal signal, his own stock price, and the stock price of his peer ("Managerial Learning Case").

2.4.1 No Learning Case

In this case, firm A's manager will decide to distribute dividend ($D_A = D_A^H$) only if his internal signal is positive ($S_A=H$) or the internal signal is uninformative ($S_A=\emptyset$) with probability equal to $\frac{1}{2}$. The prior probability to distribute dividends from firm A, that is $\Pr(D_A = D_A^H)$, is equal to:

$$\Pr(D_A = D_A^H) = \Pr(D_A = D_A^H | S_A = H) * \Pr(S_A = H) + \Pr(D_A = D_A^H | S_A = \emptyset) * \Pr(S_A = \emptyset) + \Pr(D_A = D_A^H | S_A = L) * \Pr(S_A = L) = \frac{1}{2}. \text{ Similarly, the } \Pr(D_A = \emptyset) = \frac{1}{2}.$$

2.4.2 Narrow Learning Case

In this case, the firm A's manager will decide to distribute dividend ($D_A = D_A^H$) only if her internal signal is positive ($S_A=H$) or, when her internal signal is uninformative ($S_A=\emptyset$), if her firm's stock price is high¹⁷. The prior probability to distribute dividends for firm A, that is $\Pr(D_A = D_A^H)$, is equal to:

¹⁵ This happens because his internal informativeness is very high, because he does not know that the market could provide him useful information or because he is not able to extrapolate information by prices;

¹⁶ The internal signal about his future demand obtained by the firm A's manager is Low;

¹⁷ That is, it is informative about the speculators observation of an High firm A's future demand;

$$\Pr(D_A = D_A^H) = \gamma_A/2 + \pi_A/2 * (1 - \gamma_A).$$

This probability increases as firm A's manager informativeness (γ_A) and the firm A's stock price informativeness (π_A) rise. In fact, the more informative the manager of firm A is, the more accurate the signal he obtained, and the probability of dividend distribution tends to be $1/2$ ¹⁸.

Furthermore, the more informative firm A's stock price is, the more likely the manager will have additional information about future demand, which will provide him with an indication to distribute dividends.

2.4.3 Managerial Learning Case

In the "Managerial learning case", the manager of the firm A will decide to distribute dividends ($D_A = D_A^H$) only if the internal signal is positive ($S_A = H$) or, if the internal signal is uninformative ($S_A = \emptyset$), if his firm's stock price is high.

Moreover, when both firm A's internal signal and her own stock price are uninformative, she will base his dividend policy decision on both firm B's manager's choice and the market's reaction to firm B's stock price: if firm B's manager chose to distribute dividends and her firm's stock price reacted positively, firm A's manager will distribute dividends as well ($D_A = D_A^H$); otherwise, if the market reacted negatively, firm A's manager will choose to not distribute dividends ($D_A = \emptyset$).

The logic is that if both the internal signal and her own firm's stock price are uninformative, the manager will capture information from her peer's stock price (Firm B) via the "feedback effect" mechanism generated by market reaction for determining the dividend policy.

The prior probability to distribute dividends for firm A, that is $\Pr(D_A = D_A^H)$, in this case, is equal to:

$$\Pr(D_A = D_A^H) = \gamma_A/2 - (\gamma_A - 1)/2 * (\pi_A - \pi_B * (\pi_A - 1))$$

This probability rises as firm A's manager informativeness (γ_A), the firm A's stock price informativeness (π_A), and the firm B's stock price informativeness (π_B) increase.

¹⁸ Since that $0 < \gamma_A < 1$, $\gamma_A/2$ at most it is worth $1/2$;

All else being equal, a higher informativeness of firm B's stock price will provide firm A's manager with a higher probability of distributing dividends than if firm B's stock price informativeness is low or not taken into account by him.

3. Research hypothesis

In this section, I derived the three hypotheses I will test in section 4. The three hypotheses I found are the follows: 1) when a manager observes market feedbacks the probability of distributing dividends for her company is lower; 2) uniquely in the managerial learning scenario the covariance between the two dividend policies increase with the manager (γ_B) and stock price informativeness (π_B) of firm B, while the effect of an increase in firm A's manager informativeness (γ_A) is ambiguous; 3) when the managerial learning is activated the two companies' dividend policies are more correlated than in the case of "no learning".

3.1 *The effects of managerial learning on the prior probability to distribute dividends*

If we compare the prior probability to distribute dividends in the three scenarios, we observe that the greatest probability is in the "No Learning Case". In fact, the difference between the No Learning Case and the "Managerial Learning Case" is equal to:

$$\Pr(D_A = D_A^H)_{\text{NOLEARN}} - \Pr(D_A = D_A^H)_{\text{LEARNING}} = (\gamma_A - 1) * (\pi_A - 1) * (\pi_B - 1).$$

All else being equal, increasing the information available to firm A's manager reduces the number of cases in which the manager makes a random dividend policy decision. That is, the market's information feedback will raise managers' awareness in determining a sustainable and efficient dividend policy for the company. Actually, according to Xu (2021) on the one hand, more informative stock prices lead to managers making more efficient corporate decisions, on the other hand, according to the contracting hypothesis firms' stock prices reflect the quality of managers' decisions. Furthermore, dividend distribution creates a commitment to the market that,

if not maintained, has a negative impact on the company's market value¹⁹. As a result, the market feedbacks enable managers to make more efficient long-term decisions for their companies, eliminating all cases in which they would have distributed dividends incorrectly and making them more prudential about the dividend payout policy to determine for their firms. To test this implication, in the empirical application we built a dummy variable “Learn” which is equal to 1 (that is the conditions to the learning mechanism are met) when firm A’s stock price informativeness is low (i.e., it is below the median of their 4D-Naics peers – “Lambda 1”), and when firm B’s stock price informativeness is high (i.e., it is above the median of their 4D-Naics peers - “Lambda 2”). To summarize, we can conclude the following theoretical result:

Theoretical Result 1 (Hyp1): *the prior probability of distributing dividends for a company whose manager observes market feedback is lower than for one whose manager does not observe these.*

3.2 When does managerial learning activate?

We can compute the covariance in all three cases described above to better understand the effects of managerial learning on the covariance of the two firms' dividend policies. The differences in the three scenarios are then calculated, with a focus on the "managerial learning" scenario.

3.2.1 No Learning Case

At first, consider the case where the manager of firm A fails to pay attention to the information provided by the markets. He doesn't notice it because he can't extrapolate such information or because he has a lot of internal information (γ_A is high). In this case, the covariance between the dividend policies of the two companies is equal to:

$$\text{Cov}(D_A^{\text{NO}}, D_B^{\text{NO}}) = D_A^H D_B^H \gamma_B \gamma_A (2\rho - 1)/4.$$

¹⁹ according to Bhattacharya (1979), the cost of committed dividends is the expected cost of distress financing. Therefore, good firms have a lower probability of having to obtain distress financing and so the cost of committing to pay constant dividends is lower. Hence in a world where investors conjecture that dividends are informative, undervalued firms would be willing to commit to higher dividends because the benefit to them (in terms of stock price revaluation) is greater, relative to the cost, than for overvalued firms;

As a result, in the "No Learning" case, the covariance between the two companies' dividend policies grows as the degree of correlation between the firms' demands and the informativeness of the two managers grows. Indeed, as the two managers' informativeness grows, they will rely more on their own internal signals, which will almost certainly be correlated with that of their peers. As a result, the two managers' dividend policy decisions become more correlated.

3.2.2 *Narrow Learning Case*

In this case, the manager of firm A uses both the information provided by his company's stock and the internal signal he received about his company's future demand. The covariance is then equal to:

$$\text{Cov}(D_A^{\text{NARROW}}, D_B^{\text{NARROW}}) = D_A^H D_B^H \gamma_B \gamma_A (2\rho - 1)/4$$

The covariance has the same value as in the "No Managerial Learning" case. This is because firm A's manager does not change his information source to determine his firm's dividend policy, even if she now observes its stock price to determine his firm's dividend policy. In both the "No learning" and "Narrow learning" cases he bases his decision on the signal about his future demand. In fact, in the first case (No learning), the manager of firm A made his dividend policy decision solely on his internal signal; in the second case (Narrow learning), she makes his decision on her internal signal or her stock price, which is determined by speculators based on the signal about firm A's future demand. As a result, the correlation with the information used by firm B's manager to determine his firm's dividend policy is the same in both cases. In this case, when the correlation between the firms' demands and the informativeness of the two managers increases, so does the covariance between their dividend policies.

3.2.3 *Managerial Learning Case*

When the conditions of the managerial learning are met and so the manager of firm A also observes the market feedback on his peers' dividend policy, the covariance is:

$$\text{Cov}(D_A^{\text{LEARN}}, D_B^{\text{LEARN}}) = D_A^H D_B^H (\pi_B(\gamma_A - 1)\gamma_B(\pi_A(\gamma_B + 2)/4 + 1/4(-2 - \gamma_B)) + \gamma_A \gamma_B(\rho/2 - 1/4))$$

The economic intuition is the following. As the informativeness of firm B's manager grows, the decisions she takes about the dividend policy will be more accurate and it will cause a positive reaction from speculators operating on the market. So, the feedback (in terms of market price) provided by the market will be more likely positive and consequently, the learning mechanism affects more the firm A's manager decision on his firm's dividend policy.

Therefore, an increase in the informativeness of firm B's manager implies an increase in the covariance between the two dividend policies. That is, if the informativeness of firm B's manager grows, firm A's manager will base less his decision on his internal signal (because he has a high informativeness of the signal coming from the market). As a result, she will rely more on her firm's dividend policy decision on firm B's stock price (the learning mechanism grows). This implies a greater covariance between the dividend policies because the signals through which A and B will determine their own dividend policy will be more correlated.

In terms of the informativeness of firm A's stock, an increase indicates that firm A's manager relies more on the signals of future demand provided by her own stock price and pays less attention to the price of its competitor's stock and her internal signal. This will result in a reduction of the learning mechanism and a less covariation between the two peers' dividend policies²⁰. The opposite is true if the informativeness of firm B's stock rises²¹. Furthermore, as explained above, according to the contracting hypothesis, a higher informativeness of firm B's stock price provides firm A's manager with an assessment of the quality of the decision taken by firm B's manager. Therefore, firm A's manager will pay more attention to the firm B's dividend policy decision.

Instead, as I wrote above, a raise in firm A's manager informativeness could imply two different effects on the covariance: if the firm B's manager informativeness is greater than $\frac{2}{3}$ and that of firm A's manager is lower than $\frac{1}{2}$ so an increase of the firm A's manager informativeness reduce the covariance; otherwise, the opposite is true.

²⁰ "Lambda 1";

²¹ "Lambda 2";

The logic is the following: if the firm B's manager informativeness is greater than $2/3$, then the information provided by firm B's market price is high because its manager is informed. In this case an increase in the firm A's manager's informativeness leads him to rely more on his internal signal than on the market prices. So, the information loss is very high resulting in a lower covariance between the two dividend policies. On the contrary, if firm B's manager informativeness is lower than $2/3$ the information loss will be offset by the fact that the signals of the two managers are correlated, resulting in a high covariance of the two dividend policies.

To conclude, an increase in the correlation coefficient results in an increase in the covariance between the two dividend policies. This is easily explained by the fact that the stronger the correlation between the demands of the two firms, the stronger the correlation between the two signals obtained by the two managers.

The above findings indicate that the more informative firm B's stock price is and the less informative firm A's stock price is, the more the learning mechanism is activated. In this case, the manager of firm A obtains additional information, namely the market reaction to firm B's manager's decision. This information completes firm A's manager's decision-making process regarding his firm's dividend policy, allowing him to base his decision on more than just his internal signal and stock price.

Furthermore, because the market provides feedback after the decision of firm B's manager, firm A's manager can make a decision that she would never have made if he had relied solely on internal information and the price of her stock. In this case, the manager of the firm A would have made a random or inefficient decision because both his internal signal and his firm's stock price were uninformative. To summarize, we conclude that:

Theoretical Result 2 (Hyp2): *in the managerial learning scenario the covariance between the two dividend policies increases with the manager (γ_B) and stock price informativeness (π_B) of firm B, as well as with the correlation coefficient of the firms' demands (ρ), and decreases with the stock price informativeness of firm A (π_A). Instead, the effect of an increase in firm A's manager informativeness (γ_A) is ambiguous.*

3.3 The effects of managerial learning on the covariance of firms' dividend policies

To conclude, we compared the covariance in the “Learning” and “No Learning” scenarios. The model emphasizes that learning behavior is a mechanism that reduces the randomness and raises the efficiency with which managers determine their dividend policy. In fact, observing the prices of competitors formed on markets provides managers with a set of information that they could not have obtained any other way. This implies that, in the event of a positive or negative market reaction to previous periods' dividend policy decisions by peers' companies, managers implement similar or opposite strategies rising the covariance between their dividend policies.

When such a learning is absent, however, there is a lower covariance between these dividend policies. Indeed, when the manager of the firm A decides on her firm's dividend policy without seeing market prices, she bases his decision on the internal signal she received. When she has not an informative signal she will decide randomly her firm's dividend policy, increasing the likelihood that the two managers will make different decisions. Therefore, what I find is the following:

$$\text{Cov}(D_A^{\text{LEARN}}, D_B^{\text{LEARN}}) - \text{Cov}(D_A^{\text{NO}}, D_B^{\text{NO}}) = 1/4 * D_A^H D_B^H (\pi_A - 1) \pi_B (\gamma_A - 1) \gamma_B (\gamma_B + 2)$$

Considering that this delta covariance always assumes positive values since both π_A and γ_A take values between 0 and 1, I can conclude that:

Theoretical Result 3 (Hyp3): *when managerial learning is activated the two companies' dividend policies are more correlated than in the case of “no learning”.*

4. Data and methods

4.1 Dataset construction and descriptive statistics

My dataset is built on a sample of U.S. public firms. It is formed by a couple of firms linked by Hoberg and Phillips' coefficient²².

Specifically, in each year, they compute a measure of product similarity for every pair of firms by comparing the product descriptions from the company 10-K forms.

²² Hoberg, G. and Phillips, G., 2016. Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy*, 124(5);

The measure ranges between 0% and 100% concerning the relative number of words that two firms share in their product description. The more the measure is near 100% the more the two firms have a similar product portfolio.

Then, they identified the TNIC peers of each firm by setting a threshold of minimum similarity and taking only the peers with a similarity coefficient greater than the threshold. To conclude, they computed the score I have in my dataset by computing the amount by which the pairwise score exceeded the similarity threshold for being included in the TNIC database.

Then, using the GVKEY codes of each company I matched these with financial data obtained by Compustat Dataset and Eikon Refinitiv.

I take the firm-year observations for each of the couple of firms from 2002 to 2019 based on the data available on the two datasets. I exclude firms in financial (SIC codes 4900-4999) and utility industries (SIC codes 6000-6999) because these are regulated industries with distinct dividend policies and strategic decisions.

Then, I drop all the couple of firms with less than 5 observations during the years considered.

To sum up, my sample consists of an unbalanced panel of 61.692 firm-year observations (each of them pairs two different firms) of 627 distinct firms going from 2002 to 2019. The average number of peers per firm is 10 and the average observations I have for each couple of firms is 11.

That is, during the period considered the mean number of distinct peers I pair for each firm is 10; and for each couple, I see on average 11 observations between 2002 and 2019. However, this does not mean that in each year I pair one company with all 10, since it is possible for example that one or more of these had not yet been constituted or had not yet been listed each year, but that during all the considered period I pair that company with 10 distinct peers.

The average firm's similarity²³ is 4,50%. The table below presents descriptive statistics.

²³ i.e., Hoberg and Phillips' coefficient;

Table 1 - Summary statistics

Variables	Mean	SD	p25	p50	p75	Min	Max	N
<i>Cash Dividends</i>	248.3	1,090	0	0	28.10	0	36,112	61,692
<i>Div. Payer</i>	0.392	0.488	0	0	1	0	1	61,692
<i>Cash Dividends Ratio</i>	1.351	4.714	0	0	1.395	0	145.9	61,652
<i>Size</i>	6.939	2.175	5.278	6.907	8.513	2.419	11.67	61,652
<i>Tobin Q</i>	2.183	2.007	0.984	1.664	2.698	0.083	11.76	61,652
<i>Leverage</i>	0.174	0.209	0	0.120	0.266	0	1.049	61,652
<i>Capex Ratio</i>	0.041	0.045	0.0130	0.026	0.052	0.001	0.244	61,652
<i>Profitability</i>	-3.374	20.36	-0.124	0.049	0.112	-175.6	0.470	61,002
<i>Yearly Sales Growth</i>	1.253	1.053	0.991	1.080	1.221	0.100	9.839	46,100
<i>Net Income Volatility</i>	281.5	697.6	13.09	45.43	171.0	0.686	4,429	54,770
<i>Cash Flow Volatility</i>	0.131	0.262	0.026	0.054	0.131	0.003	2.011	54,755
<i>Share Repurchase</i>	0.496	0.500	0	0	1	0	1	61,692
<i>Dummy</i>								
<i>Cash Dividend/Mrkt Cap</i>	0.010	0.030	0	0	0.0142	0	0.723	48,168
<i>Price Informativeness</i>	0.089	1.830	-1.092	0.097	1.286	-4.904	4.607	61,692

4.2 Empirical methodology

To test the theoretical results found in Section 3.2, I used a fixed effects (within estimator) model as the baseline empirical approach to account for the unobserved heterogeneity that is present in the data²⁴.

4.2.1 Empirical test of theoretical Result 1

To empirically test the prediction in TR1, I used the following regression as a baseline to see if the prior probability of distributing dividends for a firm whose manager observes market feedbacks is lower than for one whose manager does not.

$$(Eq.1) \text{ Div.Payer}_{i,t} = \alpha_i + \alpha_t + \alpha_1 \text{Learn}_{i,t} + \alpha_2 X_{i,t} + \epsilon_{i,t}$$

The dependent variable, *Div. Payer*_{*i,t*}, is a dummy that indicates whether or not the firm *i* paid dividends in year *t*. The subscripts *i* and *t* represent firm (i.e., firm A in the model), and the year, respectively. The variable we are most interested in is *Learn*_{*i,t-1*}. As a result, the "Learn" dummy variable is a linear combination of the two "Lambda".

²⁴ I check for the unobserved heterogeneity by performing an F-test on the dummies of the fixed effect model;

The set of control variables $X_{i,t}$ is primarily based on the literature and includes firm-specific control variables known to influence dividend policy decisions. Following the most common set of control variables used in the top ten financial journals when studying the effects on the payout policy of the firms - according to Mitton (2021) -, I consider the variable *Size* as a proxy of the dimension of the firm, computed as the logarithm of the total assets of firm i at time t ; as a proxy of the firm's leverage the ratio of total debt on total assets of firm i at time t (*Leverage*); as a proxy for its investment level, the variable *Capex Ratio*, computed as the ratio of CAPEX on Total Assets of firm i at time t ; and as a proxy for firm profitability (*Profitability*), the ratio between Net Income and Total Revenue of firm i at time t .

Furthermore, to account for the volatility of Net Income and Cash Flows, following Friend e Lang (1988) I computed the variables *Net Income Volatility* and *Cash Flow volatility* as the average of the standard errors of the residuals of Net Income and of Cash Flow of firm i from time t to time $t-5$, respectively. Actually, one of the major factors determining dividend payout policy is the firm's investment opportunities²⁵. Following prior studies in the literature such as Jung et al. (1996), Martin (1996), and Chen et al. (2021) I used the variables *Tobin Q*, computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t , and *Yearly Growth Sales*, computed as the ratio between the Revenue of firm i at time t and time $t-1$, as proxies of firms' investment opportunities. Even though these two variables are considered proxies of investment opportunities, they allow us to control for the fundamental value of the firm (*Tobin Q*) and its growth rate (*Yearly Growth Sales*). Finally, α_i and α_t are the fixed effects for industry and year, respectively.

I chose this model because the estimates are consistent when the unobserved heterogeneity is taken into account. In the baseline specification, I used a within-demean estimator, as well as a first-difference estimator and a probit estimator for robustness testing. Moreover, in all the specifications I winsorized the control variables at a 1% level to avoid the effects of the outliers and I scaled all independent variables by their standard deviation to obtain estimated coefficients that are directly

²⁵ See Baker and Powell (2000) to a survey of the major determinants of the dividend payout policy of the firms;

informative about the economic significance of the effects they have. That is, by construction, the coefficients measure the change in the firm i 's investment for a one standard deviation increase in the independent variables. I detail the construction of all the variables the Table 2.

Table 2 – Definition of the variables

Variable	Definition	Source
<i>Cash Dividends</i>	level of cash dividend distribution by the firm in year t	Compustat
<i>Div. Payer</i>	a dummy variable equal to 1 if the firm distributes cash dividends in year t , or 0 otherwise.	Refinitiv Eikon
<i>Cash Dividends Ratio</i>	the ratio between the cash dividend distribution by the firm in year t and its total assets	Compustat
<i>Size</i>	the logarithm of the book value of assets in year t	Compustat
<i>Tobin Q</i>	the ratio between the sum of the book value of assets plus the market value of equity minus the book value of equity of the firm in year t and the book value of equity of the firm in year t	Compustat
<i>Leverage</i>	the ratio between the long-term debt and the total assets of the firm in year t	Compustat
<i>Capex Ratio</i>	the ratio between the capex and the total assets of the firm in year t	Refinitiv Eikon
<i>Profitability</i>	the ratio between the net income and the total revenue of the firm in year t	Compustat
<i>Yearly Sales Growth</i>	the ratio between the total revenue of the firm in year t and $t-1$	Compustat
<i>Net Income Volatility</i>	the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$	Refinitiv Eikon
<i>Cash Flow Volatility</i>	the average of the standard errors of the residuals of Cash Flow of firm i from time t to time $t-5$	Refinitiv Eikon
<i>Share Repurchase Dummy</i>	a dummy variable equal to 1 if the firm repurchases its shares in year t , or 0 otherwise.	Refinitiv Eikon
<i>Cash Dividend/Market Capitalization</i>	the ratio between the cash dividend distribution and the market capitalization of the firm in year t	Compustat
<i>Price Informativeness</i>	firm-specific return variation defined as $\ln((1-R^2_{i,t})/R^2_{i,t})$ where the $R^2_{i,t}$ is that from the regression in year t of firm i 's weekly returns on market returns and the peers' value-weighted portfolio returns	Refinitiv Eikon

4.2.2 Empirical test of theoretical Result 2

The second model aims to empirically test the prediction found in Hyp2. According to this, uniquely in the managerial learning scenario, the covariance between the two dividend payout policies increases with the stock price informativeness (π_B) of firm B, as well as with the decreases with the stock price informativeness of firm A (π_A). To see if these two theoretical results are also empirically supported, I used the following fixed effects model as a baseline specification:

$$\begin{aligned} \text{(Eq.2) Cash Dividends Ratio}_{i,t} = & \beta_0 + \beta_1 \text{Cash Dividends Ratio}_{-i,t} + \beta_2 \text{Price} \\ & \text{Informativeness}_{i,-i,t} \beta_3 (\text{Cash Dividends Ratio}_{-i,t} \times \text{Price Informativeness}_{i,-i,t}) + \beta_4 X_{i,t} + \\ & \beta_5 X_{-i,t} + \varepsilon_{i,t} \end{aligned}$$

In this model, the dependent variable is a proxy for dividend policy: the ratio of Cash Dividends distributed by the firm *i* in year *t* to Total Assets in year *t*²⁶ (*Cash Dividends Ratio_{i,t}*). The structure of the model is similar to that shown in the previous section; however, to investigate the effect of increasing firm *B*'s stock price informativeness and decreasing firm *A*'s stock price informativeness, I make the proxies to measure these two parameters (*Price Informativeness_{i,-i,t}*) interact with the proxy for the company *-i*'s dividend policy (*Cash Dividends Ratio_{-i,t}*).

As in Durnev et al (2004), Chen et al (2007), and Foucault and Fresard (2014) I measure the informativeness of a firm stock price by its firm-specific return variation (or price non-synchronicity). Following Roll (1988) and Foucault and Fresard (2014) this is defined as $\ln((1-R^2_{i,t})/R^2_{i,t})$ where the $R^2_{i,t}$ is that from the regression in year *t* of firm *i*'s weekly returns on market returns and the peers' value-weighted portfolio returns. The idea is that trading on firm-specific information makes stock return less correlated with that of its peers and increases the total volatility due to idiosyncratic returns, therefore the stock price informativeness is higher when the firm-specific return variation is high.

As a result, when we interact the proxy of firm *B*'s stock price informativeness with that of the dividend policy of firm *-i* at time *t* (*Cash Dividends Ratio_{-i,t}*) we expect that β_3 will be positive and statistically significant if the theoretical finding is correct. On the contrary, when we interact the proxy of firm *A*'s stock price informativeness with that of the dividend policy of firm *-i* at time *t* (*Cash Dividends Ratio_{-i,t}*) we expect that β_2 will be negative and statistically significant.

In addition, following Foucault e Fresard (2014), having scaled all independent variables by their standard deviation the coefficient β_1 is the empirical counterpart of the covariance between firm *i* and the firm *-i*'s dividend policies and, the coefficient

²⁶ According to Mitton (2021), when considering models that study the dividend payout policy of the firms, this is the most frequently used dependent variable in the top ten finance journals;

β_3 show as this covariance change according with the two stock price informativeness in the learning scenario. This makes the interpretation of the results easier.

Finally, as in the model explained in Section 4.2.1, the vector $X_{i,t}$ includes the same set of control variables detailed above to control for the determinants that could potentially affect the dividend payout policies. Furthermore, the vector $X_{-i,t}$ includes the same set of control variables for the peer firm to take into account the peer's characteristics and dynamics. β_i and β_t are the fixed effects for industry and year, respectively.

As a robustness check, I ran a first-difference fixed effect model to test the results obtained with the fixed-effects (within estimator) model. In actuality, the first-differenced estimator is a method for dealing with the problem of omitted variables when employing panel data. The estimator is derived by conducting a pooled OLS estimation for a regression of the differenced variables, that is, instead of utilizing the inside transformation, I use the first-differenced variables in the regression. Because the intercept is differenced out, first-differenced methods cannot estimate it.

4.2.3 Empirical test of theoretical Result 3

Finally, according to Hyp3, I want to see if the dividend policies of the two firms are more correlated in the managerial learning scenario than in the "no learning" scenario. To do so, I estimated the following fixed-effects model:

$$\text{(Eq.3) Cash Dividends}_{i,t} = \gamma_i + \gamma_t + \gamma_1 \text{Cash Dividends}_{-i,t} + \gamma_2 (\text{Cash Dividends}_{-i,t} \times \text{Learn}_{i,t}) + \gamma_3 \text{Learn}_{i,t} + \gamma_4 X_{i,t} + \gamma_5 X_{-i,t} + \varepsilon_{i,t}$$

In this last case, I used as dependent variable the level of cash dividends distribution of firm i at time t , since I want to test how to change the level of the cash dividend distribution of firm i when the managerial learning is at play. As explained above, $\text{Learn}_{i,t}$ is a dummy variable that equals to 1 if the learning conditions are met. This variable interacts with the primary control variable ($\text{Cash Dividends}_{-i,t}$) to investigate if when management learning is active, the two companies' dividend policies are more correlated than in the case of "no learning".

As previously stated, γ_1 is the covariance between the dividend policies of the two companies i and $-i$ by definition, whereas γ_2 is the incremental effect on the covariance when the learning mechanism is activated. Therefore, when the dummy variable

$Learn_{i,t}$ is equal to 1²⁷, we would expect that the γ_2 to be positive and statistically significant. Furthermore, as in the previous specifications, the vector $X_{i,t}$ and $X_{-i,t}$ include for both the firms the same set of control variables detailed above to control for the determinants that could potentially affect the dividend payout policies γ_i and γ_t are the fixed effects for industry and year, respectively.

Even though the specification is robust to various controls and utilizes clustered standard errors at the firm-pair and year levels, my regression includes all terms at time t . This is due to the fact that, despite the fact that the theoretical model is divided into three periods, the effect of learning is not realized in the succeeding periods. Managers, in reality, utilize current²⁸ stock prices rather than past stock prices of their counterparts to complete their knowledge sets and make decisions.

This might cause endogeneity issues, especially in terms of reverse causality. Indeed, it is feasible that the firm i 's manager bases her dividend payout policy on the company $-i$'s payout policy decisions and the price of its stocks. However, it should also work the opposite way. In reality, the model's logic would already mitigate this issue. Firm $-i$ is, in fact, a competitor of firm i and vice versa. However, to avoid reverse causality concerns from affecting the estimate and to avoid endogeneity issues, I adopted Anderson and Hsiao's (1981) IV approach for static panel models.

Following the authors, I instrumented the first endogenous variable ($Cash Dividends_{i,t}$) using its second lag and its second lagged difference in the first stage. Moreover, since I am interested in the interaction of this variable with that of the learning ($Cash Dividends_{-i,t} \times Learn_{i,t}$)²⁹ I instrument this interaction in the same way.

Then, in the second stage, I used the fitted values of $Cash Dividends_{-i,t}$ and $Cash Dividends_{-i,t} \times Learn_{i,t}$ obtained in the first stage for estimating the same model in (Eq. 3) with standard errors clustered at the firm-pair level.

²⁷ For more details about the dummy $Learn_{i,t}$ see the Section 4.2.1;

²⁸ it means that they make their decisions based on price changes that occurred during the same year. De Cesari and Huang-Meier (2015), for example, state that managers observe abnormal returns and informativeness of prices in the quarter before their dividend announcement;

²⁹ in fact, we want to test if the learning mechanism increase the covariance between the dividend policies of the two firms;

5. Results

In my first set of multivariate analyses, in Table 3 I report the results of the estimates for various specifications of the (Eq. 1) about the Hyp1.

Table 3 - Fixed effect model regressions – baseline specification

This table reports the estimates of the effect of the learning mechanism on the probability to distribute the cash dividend of a company. The dependent variable in this baseline specification is a dummy variable that indicates whether or not the firm i paid dividends in year t . *Learn* is a dummy variable that indicates whether or not the learning mechanism is active (dummy is equal to 1), that is when the informativeness of firm A's stock price is low and the informativeness of firm B's stock price is high. Size is the logarithm of the Total Assets of the firm i at time t . Leverage is the ratio of total debt on total assets of firm i at time t . Tobin Q is the proxy of firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . Yearly Sales Growth is the proxy of the firm's growth rate and is computed as the ratio between Total Revenue of firm i at time t and the same variable at time $t-1$. Capex Ratio is the ratio between the capital expenditure of the firm i at time t and its total assets. Net Income Volatility is the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$. Cash Flow Volatility is the average of the standard errors of the residuals of the Cash Flows of firm i from time t to time $t-5$. ROA is the ratio between the earnings before extraordinary items of firm i at time t and its total assets. In Columns (1) and (2) I used a fixed effects within estimator with only firm pair (Column (1)) and with both firm pair and year (Column (2)) clustered standard errors, respectively. In Column (3) I used a Pooled OLS model with double fixed effects. In Column (4) I estimated the baseline specification using a random effects model. All control variables are winsorized at both 1% and 99% and scaled by their respective standard deviation. Each regression includes a separate intercept. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variable	<i>Div. Payer_i</i>			
	(1)	(2)	(3)	(4)
<i>Learn_i</i>	-0.009*** (0.003)	-0.009* (0.005)	-0.009* (0.004)	-0.009*** (0.003)
<i>Size_i</i>	-0.044*** (0.010)	-0.044** (0.020)	-0.044** (0.020)	-0.044*** (0.011)
<i>Leverage_i</i>	0.009*** (0.003)	0.009 (0.005)	0.009 (0.005)	0.009*** (0.003)
<i>Tobin Q_i</i>	-0.010*** (0.002)	-0.010 (0.007)	-0.010 (0.008)	-0.010*** (0.003)
<i>Yearly Sales Growth_i</i>	0.015*** (0.002)	0.015* (0.008)	0.015* (0.008)	0.015*** (0.002)
<i>Capex Ratio_i</i>	-0.002 (0.003)	-0.002 (0.007)	-0.002 (0.007)	-0.002 (0.003)
<i>Net Income Volatility_i</i>	-0.022*** (0.004)	-0.022*** (0.006)	-0.022*** (0.005)	-0.022*** (0.004)
<i>Cash Flow Volatility_i</i>	0.039*** (0.003)	0.039*** (0.009)	0.039*** (0.009)	0.040*** (0.004)
<i>ROA_i</i>	-0.023*** (0.002)	-0.023** (0.010)	-0.023* (0.011)	-0.023*** (0.002)
Constant	0.522*** (0.033)	0.522*** (0.068)	0.370 (0.289)	0.370*** (0.034)
Observations	45,868	45,868	45,912	45,912
R-squared	0.815	0.815	0.815	-
Firm Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
S.E. Cluster	Firm Pair	Firm Pair & Year	Firm Pair	Firm Pair & Year

The first two columns present estimates for our baseline specifications (fixed effects within estimator model), with standard errors clustered solely at the firm pair level in Column (1) and at both the firm pair and year level in Column (2).

I used as dependent variable a dummy (*Div. Payer_i*) that indicates whether or not the firm *i* paid dividends in year *t*. *Learn_i* is a dummy variable that indicates whether or not the learning mechanism is active (the dummy is equal to 1), that is when the informativeness of firm A's stock price is low and the informativeness of firm B's stock price is high.

In both columns, we found that when the managerial learning conditions are recognized, the a priori probability of firm *i* to distribute cash dividends is lower than in the "no learning scenario," as predicted by Hyp1 of my theoretical model. Precisely, a one standard deviation increase in the variable *Learn_i* resulted in a 0.85% decrease in the probability of firm *i* to distribute dividends. In both Columns (1) and (2), this effect is strong and statistically significant. In the remaining columns of Table 3, I performed several robustness checks to confirm the baseline result. Although using an F-Test I established that in the data there is unobserved heterogeneity³⁰, in Column (3) I show a Pooled OLS regression using standard errors clustered at firm pair level (Column (3)). The outcome does not affect the baseline specification's findings. Finally, I show the estimated results using a random effects model in the last column. Using Hausman's test, however, I proved that this model was less significant than the fixed-effects model used as a baseline. The random effects model also generates a significant negative coefficient associated with the variable *Learn*.

In Table 4 I performed further robustness checks to try to confirm the results obtained in the baseline specification.

Specifically, in the first column, I investigated whether the effect of the learning was limited to cash dividend distributions or applied to the entire payout policy of the company.

Interestingly, using as a dependent variable a dummy equal to 1 if firm *i* repurchased treasury shares in year *t* and 0 if it did not, I found that when considering the repurchase of treasury shares, the effect remains negative but loses statistical significance.

³⁰ and so, the fixed-effects model fit well in our framework;

Table 4 Robustness checks – Change dependent variable, First Difference Approach and Wooldridge Test for esogeneity

This table reports the estimates obtained trying to give more robustness to the baseline findings. In Column (1) I used as dependent variable a dummy that is equal to 1 if the firm i in year t has repurchased their shares to check if changing the dependent variable the baseline results hold. In Column (2) I used a probit model with double fixed effects (firm pair and year). In Column (3) I used a probit model with double fixed effects (firm pair and year) adjusted for the bias of incidental parameter problem according to Fernandez-Val and Weidner (2016). In Column (4) I used a First-Difference Approach, trying to fix endogeneity problems, in which the dependent variable is the same of the baseline specification, that is a dummy variable that indicates whether or not the firm i paid dividends in year t . *Learn* is a dummy variable that indicates whether or not the learning mechanism is active (dummy is equal to 1), that is when the informativeness of firm A's stock price is low and the informativeness of firm B's stock price is high. *Size* is the logarithm of the Total Assets of the firm i at time t . *Leverage* is the ratio of total debt on total assets of firm i at time t . *Tobin Q* is the proxy of the firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . *Yearly Sales Growth* is the proxy of the firm's growth rate and is computed as the ratio between the Total Revenue of firm i at time t and the same variable at time $t-1$. *Capex Ratio* is the ratio between the capital expenditure of the firm i at time t and its total assets. *Net Income Volatility* is the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$. *Cash Flow Volatility* is the average of the standard errors of the residuals of the Cash Flows of firm i from time t to time $t-5$. *ROA* is the ratio between the earnings before extraordinary items of firm i at time t and its total assets. In Column (5) I used a fixed effects model with a first-difference estimator in which I used all the control variables used in the baseline specification and their forward variable at time $t+1$. In Column (4) I performed an F-Test at the forward variables estimated in Column (5) to verify the strict exogeneity of the model I used. All control variables are winsorized at both 1% and 99% and scaled by their respective standard deviation. Each regression includes a separate intercept. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A - Dep. Variable	Share Rep. Dummy _{i}		Div. Payer _{i}		
	(1)	(2)	(3)	(4)	(5)
<i>Learn_{i}</i>	-0.0113 (0.00924)	-0.104** (0.0425)	-0.0810* (0.0459)		-0.0141* (0.00802)
<i>Size_{i}</i>	-0.00290 (0.0232)	-0.215** (0.105)	-0.173* (0.0927)		-0.0365 (0.0428)
<i>Leverage_{i}</i>	-0.0122 (0.00839)	0.149*** (0.0270)	0.121*** (0.0280)		0.0213*** (0.00636)
<i>Tobin Q_{i}</i>	- 0.0388*** (0.00666)	0.161*** (0.0268)	0.130*** (0.0283)		-0.00329 (0.00843)
<i>Yearly Sales Growth_{i}</i>	- 0.0109*** (0.00337)	0.246*** (0.0174)	0.195*** (0.0191)		-0.0126 (0.00853)
<i>Capex Ratio_{i}</i>	-0.0127* (0.00715)	0.0469 (0.0291)	0.0361 (0.0299)		0.00677 (0.00646)
<i>Net Income Volatility_{i}</i>	-0.00251 (0.0136)	-0.192*** (0.0379)	-0.167*** (0.0438)		-0.00260 (0.00769)
<i>Cash Flow Volatility_{i}</i>	0.00368 (0.0116)	0.393*** (0.0224)	0.339*** (0.0210)		0.0173 (0.0182)
<i>ROA</i>	0.0427** (0.0187)	-0.275*** (0.0185)	-0.224*** (0.0231)		-0.0306** (0.0139)
<i>D.Learn_{i}</i>				-0.00451** (0.00191)	
<i>D.Size_{i}</i>				-0.0136 (0.0131)	
<i>D.Leverage_{i}</i>				0.00888*** (0.00176)	
<i>D.Tobin Q_{i}</i>				0.00380* (0.00209)	
<i>D.Yearly Sales Growth_{i}</i>				0.0101***	

				(0.00130)	
<i>D.Capex Ratio_i</i>				0.00515***	
				(0.00171)	
<i>D.Net Income Volatility_i</i>				-0.00269**	
				(0.00134)	
<i>D.Cash Flow Volatility_i</i>				0.0215***	
				(0.00270)	
<i>D.ROA_i</i>				-0.000645	
				(0.000934)	
<i>F.Learn_i</i>					0.00234
					(0.00560)
<i>F.Size_i</i>					0.0374
					(0.0406)
<i>F.Leverage_i</i>					-0.00904
					(0.0118)
<i>F.Tobin Q_i</i>					-0.0137
					(0.0102)
<i>F.Yearly Sales Growth_i</i>					-0.000827
					(0.0103)
<i>F.Net Income Volatility_i</i>					-0.000415
					(0.00835)
<i>F.Cash Flow Volatility_i</i>					-0.00388
					(0.0213)
<i>F. Capex Ratio_i</i>					0.00667
					(0.00866)
<i>F.ROA_i</i>					-0.00261
					(0.00882)
<i>Constant</i>	0.528***	-1.005		0.0676***	0.384***
	(0.0870)	(0.817)		(0.00662)	(0.0859)
Observations	45,868	12,077	12,077	34,999	34,618
R-squared	0.620			0.018	0.817
Firm Pair FE	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Firm Pair & Year	Firm Pair & Year	Firm Pair & Year	Firm Pair & Year	Firm Pair & Year
Panel B					
F-Test Forward Variables					1.08
P-Value					0.4276

This conclusion indicates that the learning mechanism would only make managers more prudent regarding the distribution of cash dividends because the payment of cash dividends distribution implies a commitment to the market which, instead, doesn't imply share buybacks.

Furthermore, according to Jacob and Jacob (2013), the decision to pursue a share repurchase plan is dependent on other factors such as taxation.

Therefore, the market will provide managers with information to take more efficient dividend payout policy decisions for their companies, eliminating all cases in which they would have distributed dividends incorrectly or randomly.

All else being equal, this reduces the probability a priori to distribute cash dividends but not to acknowledge share repurchase plans.

To make the baseline results more robust, we utilize two distinct Probit models with both cross-section and time fixed effects in Columns (2) and (3).

I decide to use a Probit and not a Logit since I am interested in average marginal effect on the variable $Learn_{i,t}$ and both the models should have given me very similar results. Then, to address the incidental parameter problem that affects the fixed effects estimators of nonlinear panel data models I used an adjusted probit model with an analytical bias correction according to Fernandez-Val and Weidner (2016). As it is possible to see from the coefficients associated with the variable $Learn_{i,t}$ in the two columns, when the managerial learning conditions are met the probability to distribute dividends for firm i will decrease.

Specifically, by computing the Average Partial Effect we found that on average the effect is to decrease the probability to distribute dividends by about 2,26%³¹.

With the aim to address the problem of omitted variables in panel data in Column (4) I used a fixed-effects model with the first-difference (FD) estimator. I run a pooled ordinary least squares (OLS) estimation for a regression of the difference of the dependent variable (that is the difference in $Div.Payer_{i,t}$) from time t and $t-1$ and that of all the control variables. In this way, we avoid bias due to some unobserved, time-invariant variables.

In line with the results obtained in the baseline specification, the coefficient associated with the variable $Learn_{i,t}$ is negative and statistically significant.

Moreover, following the best practice suggested by Wooldridge (2010) and Verbeek (2017) to verify the strict exogeneity of my approach, in Column (5) I performed the same regression as the Column (4) using the same dependent variable and same controls but adding at the regression the forward controls at time $t+1$.

³¹ This is the value associated with the Average Partial Effect of the variable $Learn_{i,t}$ after performing the fixed-effects probit analytically adjusted by Fernandez-Val and Weidner (2016). This value accounts for the bias that would occur if we used an ordinary probit model with fixed effects at both the firm pair and year levels. In our case, the non-adjusted coefficient would have been 2,46% and so the bias would have been very small as a result of the large number of periods and observations;

If the strict exogeneity assumption holds all the forward control variables should have nonsignificant coefficients and their F-Test should accept the null that are jointly equal to 0.

According to the exogeneity assumption, all the forward control variables are not statistically significant and the F-Test value in Panel B of Table 4 strongly accepts the null that these variables are jointly equal to 0. So, the above results can be interpreted as quasi-causal.

In Table 5, I empirically test the theoretical finding Hyp2, according to which uniquely in the managerial learning scenario the covariance between the two dividend policies increases with the stock price informativeness of firm B and decreases with the stock price informativeness of firm A.

In the Columns (1) to (3) using a fixed-effects model with a within estimator, I tested whether an increase in the stock price informativeness of firm B resulted in a higher correlation between the two firms' payout policies according to the learning scenario. First, in Columns (1) and (2), I test this result using the baseline dependent variable *Cash Dividend Ratio_i*, which is the ratio between firm i's cash dividend distribution at time t and its Total Assets. Since I scaled all the independent variables for their standard deviation, the coefficient associated with the variable *Cash Dividends Ratio_i* identifies the covariance between the dividend payout policies of firms i and -i.

As we can expect, we found a positive and statistically significant coefficient associated with this variable.

This suggest that even in the absence of price informativeness of firm -i, the covariance between the two competing firms is positively related.

However, we are interested in seeing how the rise in firm -i's price informativeness affects the covariance.

Therefore, by observing the coefficient associated with the interaction variable *Cash Dividends Ratio_{-i} x Price Informativeness_{-i}* it is possible to conclude that an increase in the stock price informativeness of firm B leads to a greater covariance between the two firms' payout policies and this effect is significant both using only firm pair clustered standard errors (Column (1)) and firm pair and year clustered standard errors (Column (2)).

Table 5 - Empirical analysis of Hyp2

This table reports the estimates obtained using a fixed effect model regression of the covariance between the dividend payout policy of competing firms on the informativeness of firm i and i 's stock prices. The dependent variable is the *Cash Dividend Ratio* which is the ratio between firm i 's cash dividend distribution at time t and its Total Assets. *Cash Dividend Ratio* $_{-i,t}$ that is the ratio between the firm $-i$'s cash dividend distribution at time t and its Total Assets. The coefficient associated with this variable is the covariance between the two firms' dividend payout policies. The interaction variable *Cash Dividend Ratio* $_{-i,t} \times$ *Price Informativeness* $_{-i,t}$ is what we are interested in. Its' coefficient shows what is the effect of an increase in the informativeness of a firm $-i$'s stock price on the covariance between the two competing firms' dividend payout policy. *Size* is the logarithm of the Total Assets of the firm i at time t . *Leverage* is the ratio of total debt on total assets of firm i at time t . *Tobin Q* is the proxy of the firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . *Yearly Sales Growth* is the proxy of the firm's growth rate and is computed as the ratio between the Total Revenue of firm i at time t and the same variable at time $t-1$. *Capex Ratio* is the ratio between the capital expenditure of the firm i at time t and its total assets. *Net Income Volatility* is the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$. *Cash Flow Volatility* is the average of the standard errors of the residuals of the Cash Flows of firm i from time t to time $t-5$. ROA is the ratio between the earnings before extraordinary items of firm i at time t and its total assets. In Columns (1), (2), (4), and (5) I used a fixed effects within estimator with only firm pair (Columns (1) and (3)) and with both firm pair and year (Columns (2) and (4)) clustered standard errors, respectively. In Columns (3) and (6) I performed a robustness check using a different dependent variable, *Cash Dividend / Mrkt Cap*, that is the ratio between firm i 's cash dividend distribution at time t and its market capitalization at time t . All control variables are winsorized at both 1% and 99% and scaled by their respective standard deviation. Each regression includes a separate intercept. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Hyp2 cases	Stock price informativeness of peer firm			Stock price informativeness of own firm		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Cash Dividends Ratio</i> $_{-i}$	0.046** (0.018)	0.046* (0.025)		0.041*** (0.014)	0.041* (0.022)	
<i>Price Informativeness</i> $_{-i}$	-0.001 (0.007)	-0.001 (0.008)	-3.94e-05 (5.63e-05)			
<i>Cash Dividends Ratio</i> $_{-i} \times$ <i>Price Informativeness</i> $_{-i}$	0.016* (0.009)	0.016* (0.009)				
<i>Price Informativeness</i> $_i$				-0.002 (0.007)	-0.002 (0.018)	-7.94e-05 (0.0002)
<i>Cash Dividends Ratio</i> $_{-i} \times$ <i>Price Informativeness</i> $_i$				-0.016** (0.007)	-0.016* (0.009)	
<i>Cash Divs/Mrkt Cap</i> $_{-i}$			0.0003** (0.0001)			0.0003*** (8.82e-05)
<i>Cash Div/Mrkt Cap</i> $_{-i} \times$ <i>Price Informativeness</i> $_{-i}$			0.0002** (9.99e-05)			
<i>Cash Div/Mrkt Cap</i> $_{-i} \times$ <i>Price Informativeness</i> $_i$						-0.0001* (7.73e-05)
<i>Constant</i>	3.035*** (0.228)	3.035*** (0.342)	0.0194*** (0.004)	2.785*** (0.255)	2.785*** (0.410)	0.0114* (0.006)
Observations	39,726	39,726	36,654	39,716	39,716	34,428
R-squared	0.740	0.740	0.748	0.757	0.757	0.757
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Firm Pair	Firm Pair & Year	Firm Pair & Year	Firm Pair	Firm Pair & Year	Firm Pair & Year

On average, a one standard deviation increase in the interaction variable leads to a greater covariance between the two dividend payout policies of about 1,6 percentage points. In Column 3 I tested the robustness of the previous findings using the same fixed-effects model and the same set of control variables but changing the dependent variable. In this case, I used the variable *Cash Dividend / Mrkt Cap*, which is the ratio between the firm i's cash dividend distribution at time t and its market capitalization at time t³². According to the findings of Columns (1) and (2), we found that the coefficient associated with the interaction variable *Cash Dividends/Mrkt Cap_{-i} x Price Informativeness_{-i}* is positive and statistically significant too.

Similarly, in Columns (4) to (6), I tested the second part of Hyp2, which states that an increase in firm A's stock price informativeness leads to a lower covariance between the two firms' payout policies under the learning scenario.

Using the same rationale as above, I used as baseline dependent variable *Cash Dividend Ratio_i* in Columns (4) and (5).

In this case, however, my theoretical model predicts that the coefficient associated with the interaction variable *Cash Dividends Ratio_{-i} x Price Informativeness_i* will have a negative sign.

Indeed, the coefficient associated with this variable in Column (4) is negative and statistically significant, as predicted. This conclusion holds even when standard errors are clustered at the firm pair and year levels.

In the last columns, I checked the robustness of this result using a different dependent variable, that is *Cash Dividend / Mrkt Cap*.

The coefficient associated with the interaction variable *Cash Dividends/Mrkt Cap_{-i} x Price Informativeness_i* is negative and statistically significant in this case, confirming the baseline specification result.

As a result, we empirically confirmed the theoretical results obtained uniquely in the learning scenario, according to which when managers learn from observing their peers' stock prices, the covariance between the dividend policies of these competing firms increases with firm B's stock price informativeness and decreases with firm A's stock

³² we could think of this dependent variable as a kind of dividend yield of the firm;

price informativeness.

Finally, in Table 6, I show the results obtained by empirically estimating Hyp3, which indicates that when the managerial learning is enabled, the dividend policies of competing firms are more correlated than in the case of “no learning”.

Table 6 - Empirical analysis of Hyp3

This table reports the estimates obtained using a fixed effect model regression of the covariance between the dividend payout policy of competing when the learning mechanism is at play. The dependent variable is the *Cash Dividend* of firm *i* at time *t*. *Cash Dividend_{-i,t}* is the firm *i*'s cash dividend distribution at time *t*. The coefficient associated with this variable is the covariance between the two firms' dividend payout policies. The interaction variable *Cash Dividend_{-i,t} x Learn_i* is what we are interested in. Its' coefficient shows what is the effect of the learning mechanism on the covariance between the two competing firms' dividend payout policies. I considered the following set of control variables: *Size* is the logarithm of the Total Assets of the firm *i* at time *t*. *Leverage* is the ratio of total debt on total assets of firm *i* at time *t*. *Tobin Q* is the proxy of the firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm *i* at time *t*. *Yearly Sales Growth* is the proxy of the firm's growth rate and is computed as the ratio between the Total Revenue of firm *i* at time *t* and the same variable at time *t-1*. *Capex Ratio* is the ratio between the capital expenditure of the firm *i* at time *t* and its total assets. *Net Income Volatility* is the average of the standard errors of the residuals of Net Income of firm *i* from time *t* to time *t-5*. *Cash Flow Volatility* is the average of the standard errors of the residuals of the Cash Flows of firm *i* from time *t* to time *t-5*. ROA is the ratio between the earnings before extraordinary items of firm *i* at time *t* and its total assets. In Columns (1) and (2) I used a fixed effects within estimator with only firm pair (Column (1)) and with both firm pair and year (Column(2)) clustered standard errors, respectively. In the Column (3) I performed a robustness check using a fixed effects model with a first difference estimator. All control variables are winsorized at both 1% and 99% and scaled by their respective standard deviation. Each regression includes a separate intercept. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variable	Cash Div _i (1)	Cash Div _i (2)	D.Cash Div _i (3)
<i>Cash Div_{-i}</i>	35.59*** (12.85)	35.59*** (7.639)	
<i>Learn_i</i>	-18.20** (7.989)	-18.20 (18.34)	
<i>Cash Div_{-i} x Learn_i</i>	12.32** (5.510)	12.32* (6.599)	
<i>D.Cash Div_{-i}</i>			-7.952 (28.41)
<i>D.Learn_i</i>			-31.10 (21.14)
<i>D. Cash Div_{-i} x Learn_i</i>			35.77 (36.23)
<i>Constant</i>	231.8*** (87.65)	231.8* (128.1)	6.740 (10.44)
Observations	39,726	39,726	29,186
R-squared	0.771	0.771	0.043
Controls	Yes	Yes	Yes
Firm Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
S.E. Cluster	Firm Pair	Firm Pair & Year	Firm Pair & Year

To do so I used a fixed effect model with a within estimator in Columns (1) and (2). In the baseline specification, I used as a dependent variable the levels in cash dividend distributions of firm i and $-i$ at time t . This is because I want to take into consideration the change in the level of cash dividend distributions of firm i compared to that of the firm $-i$. If my theoretical model's results are correct, we can expect the coefficient of the *Cash Dividends_{-i} x Learn_i* interaction variable to be positive and statistically significant when the conditions for activation of the learning mechanism are met.

In fact, the coefficient in Column (1) is positive and statistically significant, just as predicted. This conclusion holds up when standard errors are clustered at the firm pair and year levels, as shown in Column (2). The covariance between the two companies' dividend payout policies is already positive and significant, as demonstrated by the coefficient associated with the *Cash Dividend_i*.

This verifies the findings of Adhikari and Agrawal (2018) about the peer effect on dividends across industries. However, when the conditions that trigger the learning mechanism are met, this covariance increases by approximately 34.6% compared to the no-learning scenario.

This effect is economically relevant and is in line with and expands the one found by De Cesari and Huang-Meier (2015) which shown that managers “listen to the market” since corporate events and changes in corporate policies are sensitive to market reactions. However, this result is the first in the literature that provides a mechanism³³ through which this is possible.

In Column (3), I used a fixed-effects model with the first-difference (FD) estimator and the same set of control variables as in the baseline specification to see if the baseline estimates are robust to the problem of omitted variables in panel data.

As it is possible to see in the table, the coefficient associated with the interaction variable *Learn_{i,t} x Cash Dividends_{-i,t}* shows, it is positive but is no longer statistically significant. This might be because, although my results are robust to various control variables related to the two firms' dividend policies, a reverse causality problem would occur in this model.

Indeed, the company I 's manager may observe the company $-i$'s payout policy

³³ that is the learning from peers' mechanism;

decisions and the price of its stocks to determine her dividend payout policy. But it should also work the other way around. Therefore, to address the reverse causality issue that could bias my estimates I used an IV approach for the static panel model according to Anderson and Hsiao (1981).

In the first stage, following them, I instrumented the first endogenous variable (*Cash Dividends_i*) using its second lag and its second lagged difference.

Moreover, since I am interested in the interaction of this variable with that of the learning (*Cash Dividends_i x Learn_i*) I instrument this interaction in the same way. Then, in the second stage, I used the fitted values of *Cash Dividends_{i,t}* and *Cash Dividends_{i,t} x Learn_{i,t}* obtained in the first stage.

The results I obtained are those in Table 7.

To begin, I used a fixed effect model with a within estimator to compute the regressions in the first three columns. By examining the results of first-stage regressions (Columns (1) and (2)), it is possible to confirm how all of the variables used as instruments are relevant in first-stage estimation. Furthermore, looking at the results in Column (3), we can see that, similarly to the baseline specification, the coefficient associated with the interaction variable *Cash Dividends_i x Learn_i* is positive and statistically significant.

This would suggest that while the learning mechanism is active, the covariance between competing firms' cash dividend distributions is larger than when managers do not learn from the market.

Furthermore, we can see from the three key statistics that indicate the accuracy of the estimations that these estimates are statistically quite strong.

Table 7 – IV Approach

This table reports the estimates obtained using Anderson/Hsiao IV approach to instrument the endogenous variables *Cash Div_i* and *Learn x Cash Div_i*. In Columns (1) to (3) I used a fixed effect model with a within estimator. In Columns (4) to (6) I used a fixed effect model with a first difference estimator. In Columns (1), (2), (4), and (5) there are the estimates of the first stages. In Columns (3) and (6) there are the estimates of the second stages. The dependent variables of the two stages are the *Cash Div* of firm *i* at time *t* (Column(3)) and its first difference (in Column(6)). *Cash Div_i* is the firm *i*'s cash dividend distribution. *L2.Cash Div_i* is the second lag of the firm *i*'s cash dividend distribution. *L2.D.Cash Div_i* is the second lag of the first difference in firm *i*'s cash dividend distribution. *L2.Cash Div_i x Learn* is the second lag of the interaction variable between the *Cash Div_i* and the *Learn_i* dummy variable, which is equal to 1 when the conditions to activate the learning mechanism are met. *L2.D.Cash Div_i x Learn* is the second lag of the first difference of the interaction variable *Cash Div_i x Learn*. The interaction variable *Cash Dividend_i x Learn_i* is that we are interested in. Its' coefficient shows what is the effect of the learning mechanism on the covariance between the two competing firms' dividend payout policies. I considered the same set of control variables of the baseline specification in Table 6, that is: *Size* is the logarithm of the Total Assets of the firm *i* at time *t*. *Leverage* is the ratio of total debt on total assets of firm *i* at time *t*. *Tobin Q* is the proxy of the firm value computed as the

ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . *Yearly Sales Growth* is the proxy of the firm's growth rate and is computed as the ratio between the Total Revenue of firm i at time t and the same variable at time $t-1$. *Capex Ratio* is the ratio between the capital expenditure of the firm i at time t and its total assets. *Net Income Volatility* is the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$. *Cash Flow Volatility* is the average of the standard errors of the residuals of the Cash Flows of firm i from time t to time $t-5$. ROA is the ratio between the earnings before extraordinary items of firm i at time t and its total assets. All control variables are winsorized at both 1% and 99% and scaled by their respective standard deviation. Each regression includes a separate intercept. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A - IV Approach	I Stage		II Stage	I Stage		II Stage
	Cash Div _{i}	Learn x Cash Div _{i}	Cash Div _{i}	D.Cash Div _{i}	D.Learn x Cash Div _{i}	D.Cash Div _{i}
<i>L2.Cash Div_{i}</i>	0.761*** (0.042)	-0.037* (0.020)				
<i>L2.D.Cash Divs_{i}</i>	0.270*** (0.058)	-0.033*** (0.010)				
<i>L2.Cash Div_{i} x Learn_{i}</i>	-0.021** (0.009)	1.025*** (0.011)				
<i>L2.D.Cash Div_{i} x Learn_{i}</i>	0.257 (0.205)	0.733*** (0.209)				
<i>Cash Div_{i}</i>			46.07* (26.46)			
<i>Learn_{i}</i>			-17.55* (9.002)			
<i>Cash Div_{i} x Learn_{i}</i>			19.81*** (7.507)			
<i>D.L2.Cash Div_{i}</i>				0.324*** (0.041)	-0.075** (0.035)	
<i>D.L2.D.Cash Dividends_{i}</i>				-0.105*** (0.018)	-0.065*** (0.018)	
<i>D.L2.Cash Div_{i} x Learn_{i}</i>				-0.013*** (0.005)	1.032*** (0.010)	
<i>D.L2.D.Cash Div_{i} x Learn_{i}</i>				0.019 (0.079)	0.739*** (0.168)	
<i>D.Cash Div_{i}</i>						115.4*** (41.52)
<i>D.Learn_{i}</i>						-22.23* (11.73)
<i>D.Cash Div_{i} x Learn_{i}</i>						6.784* (3.929)
<i>Constant</i>						13.91*** (4.136)
Observations	25,724	25,724	25,724	20,014	20,014	20,014
R-squared			0.011			0.005
Number of id_couple	4,578	4,578	4,578	4,492	4,492	4,492
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Fim Pair	Fim Pair	Fim Pair	Fim Pair	Fim Pair	Fim Pair

Panel B – Test IV Approach		
Kleibergen-Paap rk LM statistic	192.474***	119.054***
Chi-sq(3) P-value	0.000	0.000
Kleibergen-Paap rk Wald F statistic	89.141***	16.921***
5% ID test critical value	11.04	11.04
Hansen J statistic	5.728*	0.016
Chi-sq(2) P-value	0.057	0.991

In reality, we reject the null hypothesis of the Kleibergen Paap rk LM statistic meaning that the equation is not underidentified. Furthermore, about the Weak Identification test, we cannot use the F-statistic rule of thumb proposed by Stock and Yogo (1997) since we have more than one endogenous variable; therefore, we have to see the Kleibergen Paap F statistic which rejects the null hypothesis for weak instruments. Finally, we strongly accept the null hypothesis of the Hansen J-statistic test that the over-identifying restrictions are valid with a p-value of 0,974.

Finally, to strengthen the results found, in the last three columns, I used a fixed effects model with a First Difference estimator to replicate the IV approach used in the first three columns. As in the previous situation, all of the instruments are statistically significant in the first-stage regressions computed in Columns (4) and (5). Moreover, in the second stage (Column (6)) I found that the coefficient associated with the first difference of the interaction variable $D.Cash Div_{-i} \times Learn_i$ is positive and statistically significant validating the conclusion reached in the previous three columns and arising from our theoretical framework.

Based on these findings, we can conclude that when the learning mechanism is active, the covariance between competing companies' dividend policies increases, and it could also be interpreted as a quasi-causal link.

6. Conclusions

Stock prices aggregate information from a huge number of different investors operating on the financial markets, thereby allowing real decision-makers to infer previously inaccessible information to enhance their decision-making process.

Although this information affects a big number of real decisions, a large and growing literature show as firms' managers learn from their own stock prices and from that of their peers when making various strategic decisions.

The objective of this paper is to investigate the impact of the learning mechanism on the decision-making process of firms' managers regarding their payout policy.

To achieve this, I developed a theoretical model that produced three significant results, which I empirically tested using data from 629 US firms from 2002 to 2019. Firstly, I found that all else being equal, when a firm's manager learns from market feedback, her firm's probability of distributing dividends is lower than for a company whose manager does not learn from market information. Secondly, and uniquely in the managerial learning scenario, the covariance between the dividend policies of the two peers' companies increases with the stock price informativeness of firm B (π_B). On the other hand, it decreases with the stock price informativeness of firm A (π_A), while the effect of an increase in firm A's manager informativeness (γ_A) is ambiguous. Lastly, when managerial learning is present, the covariance between the two dividend policies is larger than in the absence of learning.

The two key economic implications emphasized by the model are: 1) despite dividend policy decisions following a different logic than that of investments, the learning mechanism still affects payout policy managers' choices and increases the covariance between peers' dividend policies. This suggests a "benchmark to peers" behavior that is novel in the literature on dividend payout decisions; 2) the learning mechanism also reduces the inefficiency with which managers determine their dividend policy.

In fact, the observation of peers' stock prices provides managers with a set of information (such as its' firm product market, or the state of the economy) that they would not have otherwise.

This results in managers implementing similar or opposite strategies in response to the market reaction to previous periods' dividend policy decisions by peers, thus

increasing the covariance between dividend policies. Conversely, in the absence of learning, the lower covariance between dividend policies is due to managers making more random decisions. These findings are consistent with and extend those of De Cesari and Huang-Meier (2015) and Adhikari and Agrawal (2018).

As a result, we can conclude that managers who benchmark against their peers' decisions and observe their stock market prices when deciding their firms' payout policy can gain a competitive advantage by acquiring fundamental information to make sustainable, efficient, and accurate dividend policy decisions. According to this, a company's manager should consider the dividend payout strategy used by competitors and supported by the market when determining the best dividend payout strategy for her company.

Additionally, according to Edmans et al (2019), investors tend to seek out companies with the best performance among competitors in the same industry. By standardizing cash dividend distributions, managers can more easily compete in remuneration to investors with their rivals.

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Chapter 4: Common ownership and payout policy in the European context

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Abstract

This study employs empirical analysis to investigate the relationship between common ownership and firms' payout policy. Utilizing a unique and novel dataset comprising ownership information for 4595 European firms from 1998 to 2021, I established that a rise in the level of common ownership leads to an increase in shareholder remuneration, as reflected in the payout policy. Notably, I discovered that this effect is primarily driven by an increase in firms' share repurchase programs, rather than cash dividend distribution. Furthermore, the effect persists even in family firms where the CEO and Chairman of the Board of Directors do not overlap and is stronger in cases where the degree of institutional investor ownership is higher. These results were confirmed through a cross-industry analysis using a fixed-effects model and a diff-in-diff approach, where financial institutions' mergers were employed as a quasi-natural experiment.

Keywords: payout policy, real decision makers, common ownership, institutional investors, corporate governance, family firms,

1. Introduction

The phenomenon of common ownership arises when investors own a stake in one or more firms in the same industry¹. The increase in the availability of passive investment vehicles, such as ETFs, which passively replicate stock indices, has resulted in a rise in institutional and non-institutional investors holding significant stakes in multiple companies in the same industry, leading to a significant increase in the degree of common ownership over time².

As a result, a new line of literature has emerged that examines the implications of common ownership on firms' strategic decisions.

Several studies, such as Azar (2012), Azar et al. (2018), Banal-Estanol et al. (2021), and Koch et al. (2021), focused on the potential anti-competitive effects of common

¹ see Backus et al. (2021) for an analysis with an historical perspective of the common ownership in America or Schmalz (2021) for a complete and recent review of the literature;

² my sample shows that the number of cross held firms increase from 711 (55,8% of the sample) in 1998 to 3103 (67,5% of the sample) in 2021;

ownership, with conflicting findings.³ Shy and Stenbacka (2020) focused on a welfare analysis of the phenomenon. They developed a theoretical model showing that the socially optimal degree of common ownership is determined by the degree of risk aversion and the relative weight assigned to consumer surplus associated with final good consumption compared to returns on saving via institutional investors. In contrast, Flath (1989), Fiocco (2016), and Hariskos et al. (2022) studied the effect of increasing cross-shareholding across vertically integrated value chain companies finding that it increases overall output and product prices.

Hennig et al. (2022) investigated the determinants of common ownership finding that it is driven by an information-based and a competition-based perspectives, while Jang et al. (2022) explored the effect of common ownership on share price informativeness and investment-to-Q sensitivity, demonstrating that common ownership can enhance information production and influences corporate investment decisions by improving price informativeness.

However, to the best of my knowledge, this is the first paper that examines the influence of common ownership on firm payout policies⁴.

Managers typically set their firms' payout policies based on investment opportunities and the capital structure target, but the payout policy also helps them to control shareholder remuneration and reduce agency costs between management and shareholders.

According to Edmans et al. (2019), a portfolio of common owners may be viewed as composed of groups of firms belonging to the same industry. As a result, in the event of a negative liquidity shock, common shareholders must decide which firms to maintain and which to sell in order to meet the liquidity requirements. Therefore, the worst-performing companies will be sold first, leading managers of peers firms in common investor portfolios begin to compete with one another to raise returns for their shareholders, and to minimize the so-called "exit-threat" (that is the opportunity for relevant investors to sell securities of firms, lowering the price of the stocks).

³ See for example Gilie et al. (2021), Lewellen and Lowry (2021) or Lewellen and Lewellen (2022);

⁴ Di Giuli et al. (2021) found that increasing common ownership leads to a stronger positive relationship between firms' dividend yield in a common owner's portfolio. They did not, however, take into account the overall impact of increasing common ownership on company payout policy decisions;

In reality, the exit of one or more common owners from the firm's capital (in our baseline scenario, that own at least 1% ownership in the firm) implies a dramatic decrease and increased volatility in the firm's stock price, as well as a loss of wealth for the other shareholders of the firm.

By committing her company to a predetermined payout policy, the firm's manager also indirectly intensifies the monitoring channel, reducing agency costs between management and shareholders⁵.

Thus, by conducting an across-industry study with a unique and previously unexplored dataset containing ownership information for 4595 European companies from 1998 to 2021, my research tries to empirically investigate the influence of common ownership on corporate payout policy.

Using a multivariate fixed effects model, I found that increasing the percentage of common ownership leads to an increase in shareholder remuneration in terms of payout policy⁶.

Specifically, an increase of one standard deviation in common ownership is associated with an increase in shareholders' remuneration in terms of dividend payout ratio⁷ of about 0.3%. In terms of real economic significance, this means an increase in the amount of dividends distributed or shares repurchased of more than € 13 million per year for each firm, resulting in a yearly increase of around € 60 billion in the cash dividend distribution and share repurchases in the sample.

This outcome is consistent with alternative specifications that employ different proxies for the payout policy and the firm's degree of common ownership, as well as a variety of control variables related to the dividend payout policy of the firm.

A noteworthy finding is that this effect is driven by an increase in the firms' share repurchase program rather than a cash dividend distribution. This could be explained by the fact that it gives managers greater flexibility and does not necessitate a strong commitment to the market, thus allowing them to enhance shareholder returns more adaptable.

⁵ This because a more aggressive payout strategy fosters a strong commitment to shareholders and the market. See Bhattacharya (1979);

⁶ i.e., the sum of cash dividends distribution and share repurchases programs;

⁷ That is *Dividend Payout/TA*, see the Table I in Appendix;

Additionally, Fichtner (2020) suggests that institutional investors, particularly active hedge funds, tend to demand measures to increase short-term shareholder value, such as special dividends or share repurchases, after acquiring a significant stake in a company. In light of this, I investigated how the extent of institutional investor ownership in the company affects these findings.

I found a positive relationship between the degree of institutional investor ownership and the firm's payout policy, and importantly, this conclusion does not hold in the absence of institutional investor ownership⁸.

Furthermore, to fill the gap in the literature regarding the relationship between common ownership and family firms, I explored whether this impact persists in family-owned firms.

Using the same methodology as the baseline specification, I found that the relation in family-owned firms is still positive and statistically significant.

However, I demonstrated that this effect is caused not by the type of company but by its governance. By employing a dummy variable to proxy for the CEO's independence from the Board of Directors, I find that increasing the level of common ownership in family firms with an independent CEO has a positive effect on the dividend payout policy. Conversely, the effect on family firms in which the CEO overlaps with the Chairman of the Board of Directors is negative and significant.

To the best of our knowledge, this is a novel finding that adds to the existing literature on family-owned firms and common ownership.

Finally, because investors do not invest at random, correlations between common ownership and dividend payout policies may not be causal because "reverse causality" may be at issue. Firms with more aggressive payout policies may attract investors, resulting in more overlapping ownership; on the other hand, common ownership may lead firms to have more aggressive payout policies.

To address such potential endogeneity issues typical of this framework, I follow He and Huang's (2017) approach and use a difference-in-difference method based on a quasi-

⁸ This is obviously an extreme case. However, it is important emphasizing how the presence of institutional investors in company capital affects this phenomenon;

natural experiment of financial institution mergers that result in a presumably exogenous change in the level of common ownership.

Using a 1% threshold for determining blockholdings and identifying treatments and controls⁹, I demonstrate that after institution mergers, treated firms experience an increase in payout policy to total assets of around 1.7%, which is about 7% of its standard deviation. Interestingly, depending on whether we investigate the entire sample of firms or a subsample of firms with similar dividend payout ratios, this impact may be interpreted in two ways.

In the first case, the growth experienced by treated firms leads to a convergence effect between the payout ratios of treated and controlled firms, which confirms Di Giuli et al.'s (2021) findings.

In the second case, treated firms see a significant rise in the payout policy ratio in the period after the mergers compared to the controlled companies that had similar payout ratios before the treatment.

This finding confirms previous literature and presents a new finding that contributes to the developing literature on the subject, offering a new contribution to several research areas.

The primary contribution of this paper is to demonstrate that common ownership can lead to an increase in shareholders' payout policy remuneration. My findings reveal that the "exit threat" power exerted by common owners induces firms' managers to compete with their peers to generate the greatest yield for common investors.

Notably, this is only observed in firms' decisions regarding share repurchase plans. These findings extend the stream of growing research on the implications of common ownership.

Secondly, my research is the first to do an across-industry study that takes into account the entire European context calling for research on the common ownership in Europe. In fact, prior works were mostly focused on the United States or were made in a single European country.

Third, I contribute to the body of knowledge concerning the role of institutional investors in shaping firm behavior. Previous literature has suggested that institutional investors

⁹ In the robustness check (Section 4.2) I performed the Diff-in-Diff approach using a threshold of 0,5%;

exert pressure on firm executives to pursue short-term returns, as seen in Fichtner (2020). In my study, I found a positive relationship between the level of institutional investor ownership and the firm's payout policy, indicating that the presence of institutional investors is a key driver of the impact of common ownership on dividend policy. Moreover, my method is the first in the literature that considers the impact of common ownership of both institutional and non-institutional common owners.

Finally, and in a novel way, my research sheds light on the consequences of common ownership on family-owned firms. I identified a positive relationship between an increase in common ownership and an increase in payout policy in family-owned firms. This result, however, is driven by family-owned firms with an independent CEO (that is, a CEO who is not the Chairman of the Board of Directors). This finding suggests that the impact of common ownership is dependent on the governance structure of the firm, rather than the type of firm itself.

The rest of the paper is structured as follows. Section 2 deepens the hypothesis development driving the tested outcomes and briefly explains the empirical approach used. Section 3 describes data and the variables used as a proxy of common ownership and payout policy. Section 4 shows the empirical results and the robustness check. Section 5 concludes.

2. Theoretical background and hypothesis development

As previously mentioned, according to Edmans, Levit, and Reilly (2019) investors can influence firms' decisions either through "voice", that is by a direct intervention in firms' strategic decisions (i.e., voting on the board of directors, suggesting a strategic change, or blocking a project), or through "exit", that is by selling their share in the firms and reducing the price of their stocks. Although the "voice" channel is crucial, the "exit threat channel" has a greater impact on company managers, particularly given the concentration of voting power in passive funds¹⁰ resulting from the widespread use of index funds.

In reality, one could hypothesize that the portfolio of common owners includes a large number of firms from many industries, especially if we think of institutional common

¹⁰ see "Passive fund ownership of US stocks overtakes active for first time", June 6 2022, Financial Times at the link <https://www.ft.com/content/27b5e047-5080-4ebb-b02a-0bf4a3b9bc08>;

owners¹¹. Moreover, it is worth noting that passive funds are often perceived as investors who do not actively manage their assets under management (AUM), but this is not always true. As reported by Jang et al. (2022), Blackrock, in its 2010 (2019) 10-K filings with the SEC, reported 1.19 trillion (\$1.95 trillion) in actively managed funds. Similarly, JPMorgan Chase, in its 10-K filing for the fiscal year 2018, claimed that the "majority of their AWM's [Asset & Wealth Management] customer assets are in actively managed portfolios". Therefore, characterizing common owners as passive investors seems to be largely unfounded¹². Moreover, my approach is the first to investigate the impact of common ownership generated by both institutional and non-institutional common owners, including active investors.

Considering the aforementioned points, When faced with negative liquidity shocks, common owners must decide which companies to keep in their portfolio and which to sell to address liquidity requirements. As a result, they tend to sell the worst-performing firms in each industry first. This creates a situation where managers of peer companies in common investor portfolios began competing with each other to maximize returns for their stockholders and reduce the "exit-threat".

In reality, the exit of one or more common owners from a firm's capital (in our baseline scenario, with at least 1% ownership) leads to a significant decrease in the firm's stock price, as well as increased volatility, resulting in a loss of wealth for the other shareholders of the company.

To increase shareholder returns, firm managers may implement a more aggressive payout policy aligned with their targeted return and capital structure. In fact, whether a company uses a cash dividend distribution or a share repurchase program has a different impact on its balance sheet and capital structure.

Furthermore, by implementing a more aggressive dividend policy, firm managers indirectly reinforce the monitoring channel and mitigate agency problems, since they establish a greater commitment to investors.

In fact, according to La Porta et al. (2000), following a steady dividend policy or a more aggressive share repurchase program generates a commitment toward the market and

¹¹ in my paper common investors may be not only institutional investors, but any investor who has a large investment in the capital of multiple companies in the same industry;

¹² see Hshieh et al. (2021) to explore the use of the vote of passive investors in their portfolio firms;

common owners, which minimizes the classical agency problems between shareholders and management. In addition, according to Fichtner (2020), hedge funds (the main kind of common owner) frequently demand measures to increase short-term shareholder value by paying special dividends or launching share repurchase programs after acquiring a relevant stake in the company. Therefore, following this premise, I propose the research hypothesis:

H1: an increase in common ownership leads to an increase in the shareholders' remuneration in terms of an increase in the firm's payout policy.

This encompasses not only cash dividend distributions but also share buyback plans. Management's preference for one strategy over another is typically driven by the company's current circumstances: larger, established companies typically distribute a significant portion of their earnings as dividends, while smaller, rapidly expanding firms prefer to compensate their shareholders by repurchasing their shares, which offers greater flexibility and does not imply a strong commitment to the market. Given these advantages, treasury stock buybacks are the most often used payout policy mechanism on financial markets today¹³.

Hence, managers may prefer to increase shareholders' returns through a more flexible approach. As a result, my second research hypothesis is as follows:

H2: managers will seek to enhance shareholder returns by increasing the amount of share buyback programs while reducing cash dividend distribution.

In addition, I examined the effect of an increase in institutional investors' common ownership in our framework. There is extensive and established literature on this topic, which encompasses various dynamics of firms. Mancini and Nyeso (2017), Azar et al. (2018), and Shy and Stenbacka (2020) investigated the impact of institutional investors' common ownership on peer firm competition, indicating that more common ownership led to higher prices and lower output¹⁴. Ramalingegowda et al. (2021) and Wang et al. (2023) found a negative relationship between the increase in common ownership of

¹³ for more detail, see the recent research of Zeng and Luk (2020);

¹⁴ A critique of such works can be found in Lewellen and Lowry (2021) and Koch et al. (2021);

institutional investors and earnings management, as well as the effect on corporate misconduct. However, to date, no studies have explored the effect of increased common ownership among institutional investors on dividend policy. As written above, Fichtner (2020) stated that a rise in institutional investor's stake in the firm call for measure to increase short-term shareholder value like the payment of special dividends or the launch of a share buyback program. Thus, we could expect that a larger stake in the company held by common institutional owners would intensify the effect on dividend payout policy. Hence, our third research hypothesis is:

H3: an increase in the level of common ownership among institutional investors leads to a greater impact on the shareholders' remuneration in terms of payout policy.

To conclude, there exists a significant research gap in studying the impact of common ownership on family-owned firms, despite this being the most popular type of corporate ownership worldwide¹⁵. Two of the most distinguishing features of family-owned firms are the ownership structure and the characteristics of the board of directors. Compared to non-family firms, the ultimate owner of European family firms typically controls a larger proportion of corporate ownership¹⁶.

In these types of firms, the family owner usually has a significant concentration of interests in the company and a low degree of diversification in their investment portfolio, meaning that the ultimate owner's stake generally accounts for the majority of their wealth. Therefore, if a common investor withdraws from the firm's capital, the decrease in firm value would likely have a stronger impact on the ultimate owner's wealth compared to an investor with a more diversified portfolio (generally this is true for an institutional investor).

Additionally, according to Brunninge and Nordqvist (2004), family firms are less likely to have independent directors on their boards than non-family firms. Family firms with independent directors, on the other hand, have a more active board than those without. According to Burkart, Panunzi, and Shleifer (2003), this results in an improved corporate

¹⁵ according to Tsoutsoutsura(2021);

¹⁶ according to Vieira (2020) and also validated by the characteristics found in our sample data;

governance environment and a greater ability for other stakeholder groups to assert their position. Based on these observations, it can be postulated that:

H4: increasing the level of common ownership in family firms lead to a more significant increase in the dividend policy payout compared to that of non-family firms.

and:

H5: increasing the level of common ownership in family firms with an independent CEO would lead to a more aggressive payout policy compared to family firms in which the CEO overlaps with the chairman of the board of directors (i.e., coinciding with a family member).

In the next section, I will go through the data and methodology used to develop the empirical analysis in further depth.

3. Data and Methods

3.1 Sample selection

I used a dataset of European listed firms with a market capitalization higher than € 100.000 as of December 31, 2021¹⁷. The financial data extends from 1998 through 2021. To be included in the sample a firm-year must have positive total assets and non-missing industry classification information (industries are specified at three-digit NAICS codes in this phase); the firm must also belong to an industry with at least 15 firms.

Following Foucault and Fresard (2014), Di Giuli et al. (2021), and Tayachi et al. (2021) I also exclude firms in the financial services (from 3D NAICS 521 to 525) and utilities (3D NAICS 221) from my sample because these are regulated industries with distinct dividend policies and strategic decisions.

I retrieve quarterly ownership data and financial statements information from Refinitiv Eikon from 1998 (the first year in which such data are available) to 2021.

¹⁷ I developed my dataset in collaboration with Federica De Ascentiis;

In a novel manner, the ownership data include quarterly holdings data of individual investors and corporations, governments and government agencies, and institutional investors¹⁸.

Refinitiv obtains ownership information from stock exchange filings, trade announcements, company websites, company annual statements, and financial newspapers.

My dataset tries to minimize the limitations of Thomson's Spectrum dataset, which is employed in the most of previous articles on common ownership. The Thomson Reuters Spectrum database only includes ownership disclosures reported in 13F filings, which include quarterly U.S. equities holdings by institutional investment managers with more than €100 million in assets under management (AUM). Moreover, Thomson's Spectrum database follows the so-called "as filed view", this means that it shows the holdings corresponding to the owner that filed the 13F.

On the other hand, as well as the dataset used by Banal-Estanol et al. (2021) and Banal-Estanol et al. (2022) my database reflects a "money-manager view", this means that the dataset combines one or more filings to connect the holdings to the firm that manages the investments.

Although my ownership database is not affected by the Wharton Research Data Services (WRDS) Thomson Reuters data quality data issues, I modify it following Azar et al. (2018) by aggregating the holdings of the top 10 institutional investors per AUM¹⁹ at the fund-family level because fund families' incentives are determined primarily by the value of their total assets under management and especially because the decision-making power is centralized at the fund-family level as shown by the tendency of institutional investors to exercise vote and governance at the family level.

Refinitiv Eikon considers the closing value as the value at year t-1 end date for firms that file and publish their annual financial statements between January and May of year t,

¹⁸ until date, the literature on common ownership had exclusively focused on the US institutional investors data. In my sample, the type of investors considered as "institutional" are the following: investment advisors, Sovereign Wealth Funds, Pension Funds, Banks and Trusts, Insurance Companies, Private Equity Funds, Hedge Funds, Foundation, Venture Capital Funds, Pension Funds, Endowment Fund, Institutions, Funds, Closed-End Funds, Exchange-Traded Funds;

¹⁹ I aggregate holding for the following the top 10 institutional investors per AUM as of 30/12/2022: Blackrock, State Street, Vanguard, Fidelity, Morgan Stanley, UBS Group, JP Morgan, Allianz, Goldman Sachs, Amundi, AXA Group. Source: <https://www.advratings.com/top-asset-management-firms>;

whereas, for firms that file and publish their financial statements between June and December of year t , the closing value is considered as the value at year t . Data about financial institutions' mergers are based on hand-matching of the ownership data and Refinitiv Security Data Company (SDC) Mergers and Acquisitions database.

The above sample selection process results in a final sample of 4595 firms from 19 nations in Europe (See table IV in the Appendix).

3.2 Variable measurement

3.2.1 Measuring Common-Ownership

I utilized quarterly holdings from the Refinitiv Eikon Database from 1998 to 2021 to create the common ownership variables.

The primary metric of common ownership is the so-called “profit weight” defined by

$$\kappa_{fg} \equiv \frac{\sum_i \gamma_{fi} \beta_{gi}}{\sum_i \gamma_{fi} \beta_{fi}}$$

where κ_{fg} represents the weight that firm f puts on every dollar of its industry peers' g profits in its maximization problem. Industry peers are defined as firms belonging to the same three-digit NAICS.

The “profit-weight” depends on β_{fi} and β_{gi} which reflect the fraction of the total shares outstanding of firm f and g owned by shareholder i . This primitive measure of common ownership also includes γ_{fi} , which is the Pareto weight that a firm places on its shareholders. Because this metric is not observable, much of the literature relies on the proportion control assumption, which assumes $\gamma_{fi} = \beta_{fi}$. This measure was introduced by Azar (2012)²⁰ and adopted by Azar and Vives (2021)²¹ as well as by Backus et al. (2021)²² and it is also a component of the MHHI measure of O'Brien and Salop (2000)²³.

²⁰ Azar, J., A new look at oligopoly: Implicit collusion through portfolio diversification, 2012, Ph.D. Thesis, Princeton University;

²¹ Azar, J., and Vives X., General Equilibrium Oligopoly and Ownership Structure, 2021, *Econometrica*, 89(3), 999–1048;

²² Backus, M., Conlon C., and Sinkinson M., Common Ownership in America: 1980–2017, 2021, *American Economic Journal: Microeconomics*;

²³ O'Brien, D.P., and Salop, S.C., Competitive Effects of Partial Ownership: Financial Interest and Corporate Control;

To create this measure, we began by gathering ownership data from Refinitiv Eikon of all 4595 European firms from the first quarter of 1998 to the last quarter of 2021.

Next, we created a comprehensive list of investors who invested in firms for each quarter and industry (as defined by the 3-D NAICS level) and built investor-company matrices containing ownership data.

We then aggregated the holdings of the top 10 institutional investors per AUM at the fund-family level and removed any duplicate investors from the lists.

We subsequently computed the profit weights for each firm pair in the same industry level (at both 3-D NAICS, 4-D, and 5-D NAICS levels) by averaging each row of the matrices, representing the average that each firm holds in its industry peers and each quarter. Finally, we calculated the measure for a given year by averaging across the four quarters. In robustness checks, I also use five alternative cross-ownership variables following He and Huang (2017).

I define as a blockholding an ownership share exceeding 1% of the firm's outstanding shares. With respect to He and Huang (2017) and following Banal-Estanol et al. (2022) I reduced the ownership threshold from 5% to 1% in order to avoid losing too many observations and since an investor with 1% ownership still has the incentive and bargaining power to influence strategic decisions²⁴.

Furthermore, this threshold appears to be consistent in a European setting where the percentage of companies owned by cross-owners is smaller than in the American context and where the degree of the ownership concentration is higher than US context, for more details see Becht and Roell (1999).

I define a cross-blockholder as an investor that owns more than 1% of more than one company in the same three-digit NAICS industry in the same quarter.

Following He and Huang (2017), the alternative measures of common ownership I used in my robustness tests are: *Cross Dummy*, a dummy variable that is equal to 1 if the firm is cross-held by at least one investor in any of the four quarters in a fiscal year and zero otherwise; *Num Connected* which represents the number of same-industry peers that share any common blockholder with the firm in a given quarter; *Num Cross* that is the number

²⁴ Jiang, W., Li, K., Shao, P., 2010. When shareholders are creditors: Effects of the simultaneous holding of equity and debt by non-commercial banking institutions. *The Review of Financial Studies* 23 (10), 3595–3637;

of unique blockholders that cross-hold the firm in a given quarter; *Avg Num* that is the number of same industry peers, excluded the firm into consideration, block-held by each cross-holding investor in a given quarter, and *Total Cross Own* which is the sum of the ownership shares of each cross-holding institution in a given firm for the quarter. I computed these variables at the three-digit, four-digit, and five-digit NAICS industry levels. Except for the first measure, (*Cross Dummy*) I first calculated each cross-ownership measure quarterly and then I averaged the results over the four quarters of a fiscal year to obtain the annual measures.

Furthermore, in the regressions I used the natural logarithm of one plus *Num Connected*, *Num Cross*, and *Avg Num* in order to correct for the skewness in these variables and to limit the influence of the outliers.

3.2.2 Dependent variable and control variables

In the baseline model, my main objective is to examine whether common ownership affects companies' dividend policies.

To take into account the entire company dividend policy I use as a dependent variable the sum of the firm's cash dividends and share repurchases scaled by total assets at time t (*Payout Policy*/ $TA_{i,t}$).

The set of control variables is mainly drawn from the literature. Following the most common set of control variables used in the top ten financial journals²⁵ I consider as controls the size of the firm (*Size*), computed as the logarithm of the total assets of firm i at time t as proxy of the dimension of the firm, the leverage (*Leverage*), computed as the ratio of total debt on total assets of firm i at time t as proxy of its debt level, the CAPEX Ratio (*Capex/TA*), computed as the ratio of CAPEX on Total Assets of firm i at time t as proxy of investment, the Tobin's Q (*Tobin Q*), computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t as proxy of its' value, the level of asset tangibility (*Tangibility*), computed as the ratio of Net PP&E on Total Assets of firm i at time t , Return On Asset (*ROA*), computed as the ratio between Net Income on Total Asset of firm i at time t as proxy of its profitability, the revenue growth rate (*Yearly Sales Growth*), computed as the ratio

²⁵ according to Mitton, T., 2022. Methodological Variation in Empirical Corporate Finance. *The Review of Financial Studies* 35 (2), 527–575;

between the Revenue of firm *i* at time *t* and time *t*-1 as proxy of its growth, and the standard deviation of Net Income (*Net Income Volatility*), computed as the average of the standard errors of the residuals of Net Income of firm *i* from time *t* to time *t*-5 as proxy of its earnings' volatility.

Furthermore, according to He and Huang (2017) I control for a variable specifically related to institutional ownership.

Among all the investors I first identify the institutional ones and the blockholders among them. Then I computed the sum of institutional blockholders' ownership shares in the firm for the quarter and I averaged across the four quarters of a fiscal year to obtain the variable *Block Own*.

I also control for *Inst Own* that is the average among the four quarters of a fiscal year of the percentage ownership by institutional investors in a given firm. The last control variable related to institutional ownership is *Block Dummy*, a dummy variable equal to 1 if the firm is blockheld by at least one institutional investor in any of the four quarters in a fiscal year and zero otherwise²⁶.

3.3 Summary statistics

Fig.1 shows the pattern of ownership from 2000 to 2020. As explained above, a blockholder is defined as an investor who owns at least 1% of the firm. A firm is defined as cross-held if at least one investor block held the firm and another firm in the same three-digit NAICS industry.

The graph shows that despite the percentage of common investors (yellow line) on the number of the total investors has remained steady throughout the last 25 years, the blue line shows how the fraction of European public companies cross-held in any fiscal year has increased from around 56% to 68% between 1998 and 2021, indicating that common ownership across industry competitors is becoming increasingly widespread in Europe. Furthermore, another interesting aspect is that the stake of ownership in the hands of the top three investors has increased during the same period showing that the concentration of the European firms' ownership has risen.

²⁶ Given their high correlation, these variables were not included simultaneously in the baseline specifications, which could have resulted in multicollinearity issues;

Figure 1 - Trend in ownership over time – graphical analysis

This figure plots the trend in crosssheld firms, top 3 holdings, and the number of common investors from 2000 through 2020. Crosssheld firms are those in which an investor owns at least 1% of the firm and in one its peer in the same 3D NAICS. Common investors are those that own a stake in at least two firms belonging to the same industry (3D NAICS level). Top 3 holdings is the average of the sum of the stake of the top 3 owners in the firms in my sample for each year. The blue line shows the trend of the fraction of European public firms that have at least one blockholding owner in their capital. The orange line shows the growing trend in the number of common investors in European public firms (see the right y-axis). The black line represents the average of the sum of the top 3 holdings in the European public firms. The yellow line shows the fraction of common investors on the total number of investors each year.

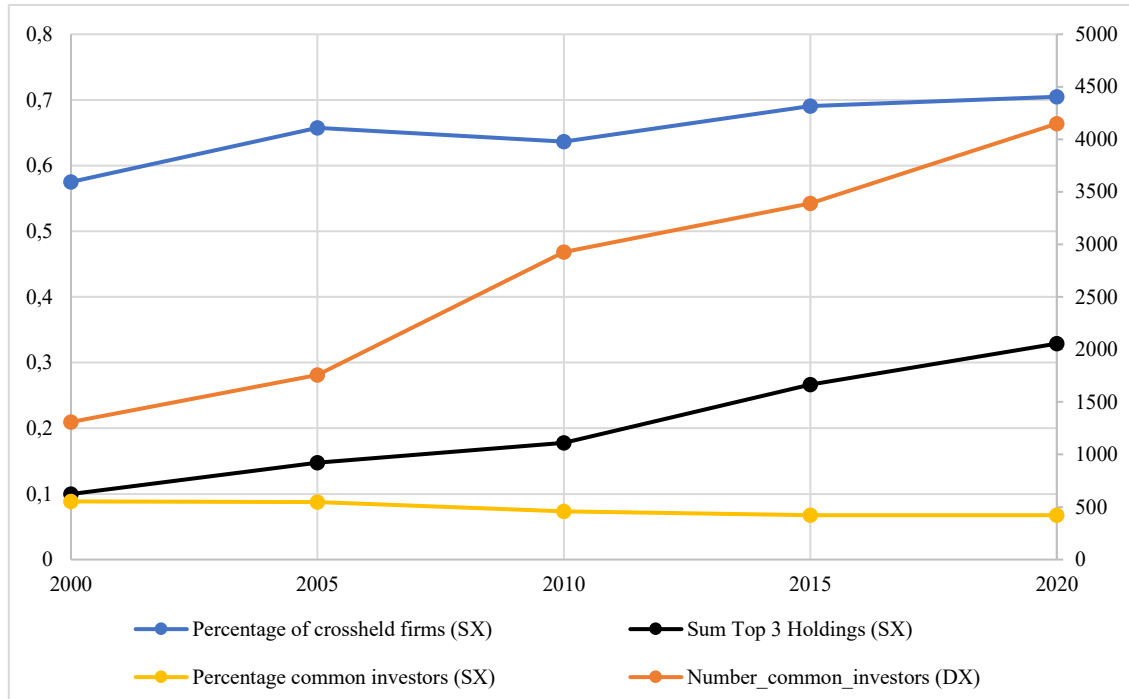


Table 1 provides a numerical detail of Figure 1.

Table 1 - Trend in ownership over time – numerical analysis

The table provides numerical details about the trend in ownership in the European context shown in Figure 1. Number of Firms shown the number of firms belonging to our sample each year. Number of total investors represents the total number of investors in each year. Number of common investors is the number of investors which own a stake in at least two firms belonging to the same industry (3D NAICS level). Percentage of common investors is the ratio between the Number of common investors and the Number of total investors. Number of single investors represents the number of investors which own a stake in only one firm in an industry (3D NAICS level). Percentage single investors is the ratio between the Number of single investors and the Number of total investors. The number of crosssheld firms is the number of public firms that have at least one blockholding owner in its capital and in one of its peers in the same 3D NAICS. Percentage of crosssheld firms is the percentage of total firms in the sample with at least on blockholding owner in its capital and in one of its peers in the same 3D NAICS. Sum top 3 holdings is the average of the sum of the stake of top 3 owners in the firms in all the sample for each year.

Year	Number of Firms	Number of total investors	Number of common investors	Percentage of common investors	Number single investors	Percentage single investors	Number crosssheld firms	Percentage of crosssheld firms	Sum top 3 holdings
2021	4595	72.831	4.695	6,4%	68.136	93,6%	3103	67,5%	39,61%

2020	3876	61.282	4.149	6,8%	57.133	93,2%	2732	70,5%	32,91%
2019	3961	66.615	4.438	6,7%	62.177	93,3%	2765	69,8%	33,73%
2018	3356	51.557	3.698	7,2%	47.859	92,8%	2367	70,5%	27,44%
2017	3594	51.530	3.600	7,0%	47.930	93,0%	2525	70,3%	29,66%
2016	3254	51.228	3.463	6,8%	47.765	93,2%	2264	69,6%	26,99%
2015	3229	50.201	3.392	6,8%	46.809	93,2%	2230	69,1%	26,64%
2014	3079	46.790	3.078	6,6%	43.712	93,4%	2117	68,8%	25,53%
2013	2932	44.597	2.972	6,7%	41.625	93,3%	1979	67,5%	24,26%
2012	2781	44.573	3.042	6,8%	41.531	93,2%	1838	66,1%	22,81%
2011	2684	44.450	3.053	6,9%	41.397	93,1%	1778	66,2%	21,48%
2010	2212	39.861	2.928	7,3%	36.933	92,7%	1408	63,7%	17,76%
2009	2532	46.258	3.339	7,2%	42.919	92,8%	1678	66,3%	20,78%
2008	2482	46.668	3.369	7,2%	43.299	92,8%	1639	66,0%	19,48%
2007	2411	46.065	3.231	7,0%	42.834	93,0%	1689	70,1%	17,91%
2006	2178	33.714	2.277	6,8%	31.437	93,2%	1415	65,0%	16,08%
2005	1973	20.073	1.758	8,8%	18.315	91,2%	1297	65,7%	14,73%
2004	1749	16.958	1.549	9,1%	15.409	90,9%	1017	58,1%	12,82%
2003	1671	16.146	1.493	9,2%	14.653	90,8%	918	54,9%	11,71%
2002	1665	16.822	1.477	8,8%	15.345	91,2%	943	56,6%	12,07%
2001	1636	16.454	1.413	8,6%	15.041	91,4%	915	55,9%	11,62%
2000	1559	14.796	1.310	8,9%	13.486	91,1%	897	57,5%	9,98%
1999	1418	12.607	1.036	8,2%	11.571	91,8%	827	58,3%	9,49%
1998	1273	10.648	831	7,8%	9.817	92,2%	710	55,8%	8,48%

Table 2 shows the distribution of block-held firms among different 3-digit NAICS industries during the most recent fiscal year of analysis, 2021.

Table 2 - Across-industry ownership detail in 2021 – numerical analysis

This table provides an across-industry detail of the ownership in 2021.

3D NAICS	Number of Firms	Numb er of cross held firms	Percen tage of cross held firms	Number common investors	Percen tage of commo n investo rs	Number single investors	Percentage single investors
111	23	6	24,0%	67	11,24%	529	89%
211	111	84	75,7%	849	14,29%	5091	86%
212	178	131	70,1%	1244	16,64%	6230	83%
213	45	33	78,6%	239	24,66%	730	75%
236	124	86	66,2%	826	28,11%	2112	72%
237	74	56	60,9%	694	27,01%	1875	73%
238	27	20	50,0%	187	13,36%	1213	87%
311	112	80	67,2%	1038	25,91%	2968	74%
312	64	37	57,8%	1226	38,38%	1968	62%
313	21	0	0,0%	21	7,37%	264	93%
315	40	23	57,5%	495	30,61%	1122	69%
316	16	10	62,5%	522	44,16%	660	56%
321	27	11	37,9%	130	19,49%	537	81%
322	43	37	80,4%	715	37,63%	1185	62%
324	21	14	66,7%	714	51,66%	668	48%
325	269	242	78,1%	2085	31,18%	4602	69%
326	45	30	60,0%	635	35,61%	1148	64%
327	51	31	58,5%	656	34,31%	1256	66%
331	68	38	55,9%	709	42,13%	974	58%
332	79	50	60,2%	720	31,83%	1542	68%
333	221	187	77,9%	1743	34,18%	3357	66%
334	330	281	78,1%	1859	18,21%	8348	82%
335	79	69	70,4%	888	26,21%	2500	74%
336	128	107	77,0%	1413	39,54%	2161	60%
337	19	12	60,0%	132	14,77%	762	85%

339	91	78	70,9%	979	34,19%	1884	66%
423	84	57	57,6%	735	32,68%	1514	67%
424	60	37	53,6%	569	23,20%	1884	77%
441	16	11	57,9%	103	13,26%	674	87%
443	18	12	52,2%	107	20,00%	428	80%
444	15	12	75,0%	226	26,22%	636	74%
445	24	22	91,7%	722	45,15%	877	55%
446	12	11	64,7%	204	30,00%	476	70%
448	28	19	55,9%	724	41,95%	1002	58%
451	11	10	58,8%	153	23,50%	498	76%
454	33	29	64,4%	282	25,52%	823	74%
481	19	14	70,0%	245	17,39%	1164	83%
483	44	33	76,7%	440	21,76%	1582	78%
488	32	24	75,0%	418	39,10%	651	61%
511	329	359	78,9%	1571	19,64%	6429	80%
512	44	24	50,0%	341	25,09%	1018	75%
515	21	11	52,4%	285	35,32%	522	65%
517	75	53	60,2%	1065	47,17%	1193	53%
518	24	24	70,6%	157	14,77%	906	85%
519	49	48	63,2%	620	18,86%	2667	81%
531	433	272	60,9%	1513	19,53%	6234	80%
532	25	14	50,0%	194	18,73%	842	81%
561	98	83	77,6%	835	25,61%	2426	74%
562	28	12	41,4%	222	28,46%	558	72%
611	14	7	38,9%	27	6,84%	368	93%
621	26	17	53,1%	408	34,72%	767	65%
622	15	7	43,8%	61	15,89%	323	84%
711	23	10	37,0%	49	8,01%	563	92%
713	36	21	58,3%	326	29,50%	779	70%
721	31	12	37,5%	230	26,05%	653	74%

722	36	28	66,7%	436	19,68%	1780	80%
# of total firms	4595						
Average values			34,7%		15,3%		41,7%

Each industry has a considerable proportion of block-held firms, with a higher concentration in Food and Beverage stores (NAICS 445), Publishing industries (except internet, NAICS 511), and Paper Manufacturing (NAICS 322). On the other hand, the Textile Mills industry (NAICS 313) does not have any cross-held firms whereas cross-held firms are less likely to be found in Crop Production (NAICS 111), in the Performing Arts, Spectator Sports, and Related Industries (NAICS 711) and in Accommodation industry (NAICS 721).

Table 3 provides summary statistics for the variables used in this study. The mean value of *Cross Dummy* is equal to 0.364 suggesting that 36,4% of the firms included in the sample are cross owned by at least one investor. The average number of same-industry peers that share at least a common blockholder is 1,25 (*Num Connected*). The mean value of the variable *Num Cross* indicates that the average number of single investors that cross-hold a firm is equal to 0,66. The average of *Avg Num* is 0,57, indicating that a firm has on average 0,78²⁷ same industry peers (excluded itself) with cross owners.

In terms of percentage terms, the average cross-blockholding (*Total Cross Own*) is 6.98%. The variable Dividend Policy on total assets has a mean value of 3,7% and a considerable variation as suggested by a standard deviation of 25,6%. Table 3 provides summary statistics for the set of control variables included in the analysis. The average firm in our sample, for example, has a Tobin's Q of 1,829, a capex ratio of 4,89%, and a leverage ratio of 20.6%. The mean value of the variable *Block Own* indicates that, on average, the ownership share held by the total number of institutional blockholders is equal to the 8,67% of the outstanding shares.

²⁷ I used natural logarithm of one plus *Num Connected*, *Num Cross* and *Avg Num* in order to correct for the skewness in these variables. See Section 3.2.1;

Table 3 - Summary statistics

Variables	mean	sd	p25	median	p75	min	max	N
<i>K 4-D NAICS</i>	0.036	1.433	0	0.0004	0.007	0	302.4	68,464
<i>K 5-D NAICS</i>	0.045	1.902	8.19e-07	0.0005	0.008	0	411.1	61,942
<i>Cross Dummy</i>	0.364	0.481	0	0	1	0	1	121,300
<i>Num Connected</i>	0.812	1.295	0	0	1.447	0	5.017	121,300
<i>Num Cross</i>	0.505	0.791	0	0	0.916	0	3.268	121,300
<i>Avg Num</i>	0.574	0.897	0	0	1.078	0	4.656	121,300
<i>Total Cross</i>	6.982	14.90	0	0	6.109	0	294.2	121,300
<i>Inst Own</i>	10.83	19.52	0	0	14.07	0	532.5	121,300
<i>Block Dummy</i>	0.412	0.492	0	0	1	0	1	121,300
<i>Top Owner Holding</i>	14.86	22.24	0	0.282	22.81	0	147.9	117,940
<i>Ceo/Chairman</i>	0.021	0.144	0	0	0	0	1	187,500
<i>Dividend Payout</i>	156.2	931.5	0.077	4.791	36.07	0	44.67	42,366
<i>Dividend Payout/TA</i>	0.037	0.256	0.001	0.015	0.035	0	33.93	41,708
<i>Dividend Payout/Mrkt Cap</i>	0.045	0.466	0.002	0.023	0.046	0	69.10	41,304
<i>Dividend Payout/Net Income</i>	1.024	6.994	0.164	0.424	0.781	0	488.2	32,901
<i>Dividend Payout/BV of Equity</i>	0.094	0.817	0.004	0.036	0.078	0	97.55	40,996
<i>Share Repurchases/TA</i>	0.029	2.153	0	0	0.001	0	385.0	47,932
<i>Cash Dividends/TA</i>	0.032	1.865	0	0.009	0.026	0	504.9	74,149
<i>Net Income Volatility</i>	85.14	523.6	1.104	4.760	25.82	0	29.28	106,120
<i>Size</i>	4.959	2.712	3.090	4.838	6.724	-1.293	12.03	108,46
<i>EBITDA Margin</i>	0.024	0.254	0.006	0.075	0.132	-1.467	0.456	90,145
<i>Tobin Q</i>	1.829	2.021	0.950	1.183	1.820	0.406	14.64	96,089
<i>Leverage</i>	0.206	0.208	0.021	0.157	0.323	0	0.970	108,420
<i>Capex/TA</i>	0.049	0.066	0.005	0.027	0.064	0	0.380	97,419
<i>Block Own</i>	8.671	16.12	0	0	10.22	0	71.80	121,300
<i>Yearly Growth Sales</i>	0.278	1.512	-0.077	0.057	0.226	-2.259	11.749	94,132
<i>Tangibility</i>	0.210	0.234	0.021	0.119	0.329	0	0.907	98,202
<i>ROA</i>	-0.229	21.923	-0.027	0.023	0.066	-1.649	0.35	108,390
<i>Total assets</i>	4,378	19,762	17.940	112.754	772.624	0	163,283	112,123

Finally, despite I don't use these variables in the baseline specification, given their high correlation with the control variable *Block Own*, average total institutional ownership (*Inst Own*) in a given firm is equal to the 10,83% of the outstanding shares and 41% of the firms included in the sample are blockheld by institutional investors (*Block Dummy*). Table 4 reports the correlation matrix for the variables.

The proxies for common ownership are positively correlated. However, the correlations across the five measures range from 0,22 to 0,95.

Moreover, also the four measures used to proxy the dividend policy of the firm are positively correlated and their correlations range from 0,05 to 0,47.

To conclude, as written above, the high correlation between the control variables *Block Own*, *Block Dummy*, and *Inst Own* doesn't allow me to utilize them in the same regression to prevent multicollinearity problems.

3.4 The European vs American Context

As previously stated, my dataset is the first to investigate the phenomena of common ownership across industries in the whole European context. Additionally, it is the first to do so using data up to December 31, 2021.

Compared to the American context²⁸ the European one is more fragmented and diversified in terms of regulation²⁹. Using the He and Huang (2017)³⁰ dataset as a comparison, we see that the median size (measured as the amount of total assets) (€112,75 mln vs \$90 mln), the median leverage (15,7% vs 12%), and the median Capex Ratio (4,1% vs 2,7%) of the firms in my sample are greater compared the firms in their dataset. On the other hand, the firms in my sample are less profitable (in terms of ROA – 8,7% vs 10,6%) and less overvalued (in terms of Tobin Q – 1.183 vs 1.361) compared to the firms in their dataset³¹. Concerning the ownership structure of the firms we can notice that the average presence of institutional investors is lower in Europe.

Actually, the mean value of the variable *Inst Own*, that is the percentage ownership by institutional investors in a given firm and in a given year, in my dataset is 10,83% versus 36.8% in their dataset.

Moreover, the value of the variables used as proxy for common ownership differs significantly across the two contexts and almost all of these variables show that there is a larger amount of connectedness among firms in the same industry in the United States than in Europe. In fact, both *Num Connected* (1,252 vs 2,285), which represents the

²⁸ see He and Huang (2017), Koch et al. (2021), Lewellen and Lowry (2021), and Jang et al. (2022);

²⁹ see Hagstromer (2022) for a recent literature review;

³⁰ the authors uses a sample of US listed firms with common stocks traded on the NYSE, NASDAQ, and AMEX during the period 1980-2014;

³¹ see Section 4 for major details about my dataset;

number of same-industry peers that share any common blockholder with the firm in a given quarter, and *Avg Num* (0,775 vs 1,043), which is the number of same-industry peers, block-held by each cross-holding investor in a given quarter, show lower value in the European context compared with the American one. The same is true for control variables *Block Own* (the sum of institutional blockholders' ownership shares in the firm for a fiscal year – 8.67% vs 11.4%) and *Block Dummy* (a dummy variable equal to 1 if the firm is blockheld by at least one institutional investor in a fiscal year – 41,2% vs 69,1%).

On the other hand, *Num Cross* (0,657 vs 0,604), which is the number of unique blockholders that cross-hold the firm in a given quarter, shows a higher value in my sample.

Although the different time horizons used to compute these values may render this comparison inaccurate³², the result that highlights this comparison is that, without a doubt, the European context is distinguished by a lower level of institutional investor presence and cross-ownership.

The fundamental reason for this is the distinctive ownership structure of European companies. In actuality, they are still heavily dominated by the top three shareholders, and their holdings are significantly greater than in the American context³³.

3.5 Baseline specification: the fixed effects model

In my baseline analysis, I assess how the increase in common ownership affects the shareholders' remuneration through an increase in the payout policy of the firm using a fixed effects model.

The management of a firm can choose to increase the remuneration of its shareholders either increasing the cash dividend distribution or rising the buyback of its shares. As explained above, in the baseline specification, I considered the entire dividend policy of the firm, that is the sum of cash dividend policy and the share repurchases of its shares. I estimate the following fixed effects model using a within estimator:

³² in fact, they only evaluate data up until 2014;

³³ in my sample, the average of the sum of the top three holdings is 30,61% vs slightly over 20% in the United States (see Figure 8 and 9 of De La Cruz et al. 2019 for further information);

$$\text{PayoutPol}_{i,t} = \alpha + \beta \text{CommOwn}_{i,t} + \gamma Z_{i,t} + \mu X_{i,t} + \delta_t + \eta_i + \varepsilon_{i,t} \quad (1)$$

where i indexes firm and t indexes time. $\text{PayoutPol}_{i,t}$ is the firm-year proxy of the payout policy. In the baseline specification I considered as a proxy the sum of the firm's cash dividends and share repurchases of firm i at time t scaled by total assets of firm i at time t ($\text{Dividend Payout}/\text{TA}_{i,t}$). $\text{CommOwn}_{i,t}$ is one of the measures I used as a proxy of the common ownership. In the baseline specification, I used the average K of the firm i computed at an industry level of 5-digit NAICS.

As explained above, I used five different measures of Common Ownership in the robustness checks following He and Huang (2017). Z is a vector of firm characteristics that may affect the Dividend Policy of a company. $X_{i,t}$ is a common ownership related control.

To conclude, in all the specifications we account for time-specific effects by including year fixed effects (δ_t) and time-invariant firm heterogeneity by including firm fixed effects (η_i). α is the intercept. I clustered standard errors at the firm and year level to correct for potential cross-sectional and serial correlation in the error terms, according to Petersen (2009).

All control variables are divided by their sample standard deviation to facilitate economic interpretation and winsorized at 1% and 99% levels.

3.6 Looking for causality: a difference in difference approach

One or more endogeneity concerns may have an impact on the fixed effects model estimations. Because investors do not invest arbitrarily, correlations between common ownership and dividend payout policies may not have a causal interpretation because "reverse causality" is at work.

In fact, firms with higher dividend payout policies may attract more investors, resulting in more overlapping ownership; on the other hand, common ownership may lead firms to have a higher dividend payout policy.

As a result, following the approach used in He and Huang (2017)³⁴, I address the potential endogeneity problems, which are typical in this framework, using a difference-in-

³⁴ For more details see section 4.1.1;

difference approach based on a quasi-natural experiment of financial institution mergers that causes a presumably exogenous change in the level of firms' common ownership³⁵. I estimate the following multivariate difference in difference equation to compare the effect of the institution merger on the treatment firms' common ownership level with that of the control firms:

$$K_{i,t} = \alpha + \beta_1 \text{Treat} \times \text{Post} + \beta_2 \text{Treat} + \beta_3 \text{Post} + \gamma Z_{i,t} + \mu X_{i,t} + \delta_t + \eta_i + \varepsilon_{i,t} \quad (2)$$

where i indexes firm and t indexes time. $K_{i,t}$ is the firm-year proxy of the level of common ownership as explained in section 3.2.1. In the baseline specification I considered as a proxy the average profit weight of firm i at time t computed at 5D NAICS. *Treat* is a dummy that equals one for treatment firms and zero for control firms.

As I describe in Section 4.2.1, I identify treatment and control firms based on He and Huang (2017).

Treatment firms are those in which one of the merging institutions had a blockholding in the quarter preceding the merger announcement, whereas the other merging party did not have a blockholding but did have at least one industry opponent from the same 4-digit NAICS in the same quarter.

Companies owned by both merging institutions during the prior quarter are eliminated. *Post* is a dummy that equals one for the post-merger period and zero otherwise. Z is the vector of firm characteristics used in my baseline regression (Equation (1)). $X_{i,t}$ is a common ownership related control.

To conclude, in all the specifications I account for time-specific effects by including year fixed effects (δ_t). Furthermore, following He and Huang (2017), I include firm-merger fixed effects (η_i) to account for time-invariant characteristics across firms within the same merger as well as time-varying common temporal trends across mergers. α is the intercept. Standard errors are robust for heteroskedasticity.

To facilitate economic interpretation, all control variables are scaled by their sample standard deviation and winsorized at the 1% level, as in the baseline model. Then, using

³⁵ Azar et al. (2018), Shy and Stenbacka (2020) and Koch et al. (2021), Lewellen and Lowry (2021), Jang et al. (2022) used the same method to address the endogeneity problems;

the logic of equation (2), I run the following model to compare the effect of the institutions' merger on dividend payout policy of treated firms with that of control firms:

$$\text{PayoutPol}_{i,t} = \alpha + \beta_1 \text{Treat} \times \text{Post} + \beta_2 \text{Treat} + \beta_3 \text{Post} + \gamma Z_{i,t} + \mu X_{i,t} + \delta_t + \eta_i + \varepsilon_{i,t} \quad (3)$$

where i indexes firm and t indexes time. $\text{PayoutPol}_{i,t}$ is the firm-year proxy of the dividend payout policy. As a proxy, I utilized the amount of the company i 's cash dividends and share repurchases at time t scaled by the firm i 's total assets at time t , as described in the baseline specification. The other variables follow the rationale outlined in equation (2).

4. Empirical Analysis

4.1 Baseline specification: empirical evidences

As stated in section 3.5, in my baseline specification, I employ a fixed effects model with a within estimator to examine how an increase in common ownership impacts shareholder remuneration via an increase in the firm's payout policy.

A company's management may decide to increase shareholder remuneration by raising cash dividend distributions or share buybacks. As previously said, I analyzed the firm's total dividend policy, which is the sum of cash dividend policy and share repurchases, in the baseline definition.

To estimate the equation (1) I used the average of the profit weights (K) at the 5-digit NAICS level. That is, in the last quarter of each year I computed the average of the profit weights of firm i with its' 5-digit NAICS peers for each firm composing the dataset. In the first three Columns (1-3) I used three different common ownership related control $\text{Block Own}_{i,t}$, $\text{Inst Own}_{i,t}$, and $\text{Block Dummy}_{i,t}$. In Column (4), following He and Huang (2017) I used all three different common ownership related controls in the same regression. However, since these three different variables have a high correlation³⁶, using all three in the same regression could lead to multicollinearity problems.

So, in my baseline specification (1) I used only $\text{Block Own}_{i,t}$ as common ownership related control variable.

³⁶ See the correlation matrix in Table 4 of this section;

Table 4 - Correlation Matrix

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.
1. Div. Payout/TA	1																										
2. K 4-D NAICS	0,01	1																									
3. K 5-D NAICS	0,01	0,80	1																								
4. Size	-0,04	0,09	0,03	1																							
5. Leverage	-0,12	0,02	0,02	0,24	1																						
6. Capex	0,00	0,07	0,03	0,62	0,12	1																					
7. Tobin Q	0,43	0,00	0,00	-0,09	-0,20	-0,03	1																				
8. EBITDA Margin	0,33	-0,01	-0,01	-0,05	-0,16	0,08	0,52	1																			
9. Block Own	0,06	0,02	0,01	0,07	-0,04	-0,08	0,06	-0,01	1																		
10. Inst Own	0,07	0,04	0,02	0,23	-0,02	0,03	0,09	0,02	0,95	1																	
11. Block Dummy	0,02	-0,04	-0,03	0,14	-0,05	-0,01	0,05	0,01	0,37	0,39	1																
12. Num Cross	0,08	0,05	0,02	0,32	-0,05	0,05	0,15	0,05	0,69	0,75	0,47	1															
13. Num Connected	0,06	0,03	0,01	0,34	-0,05	0,07	0,14	0,02	0,49	0,56	0,45	0,86	1														
14. Cross Dummy	0,05	0,00	-0,01	0,26	-0,04	0,08	0,10	0,05	0,37	0,41	0,61	0,68	0,66	1													
15. Avg Num	0,05	0,02	0,00	0,35	-0,03	0,10	0,12	0,01	0,35	0,42	0,45	0,72	0,95	0,67	1												
16. Total Cross	0,07	0,06	0,03	0,16	-0,02	-0,01	0,09	0,02	0,70	0,73	0,22	0,76	0,58	0,41	0,44	1											
17. Div. Payout/BV of Equity	0,47	0,01	0,00	0,01	0,04	0,01	0,22	0,14	0,04	0,05	0,01	0,05	0,02	0,02	0,01	0,04	1										
18. Div. Payout/Net Income	0,22	0,00	0,01	0,01	0,03	0,00	0,00	-0,02	0,02	0,02	0,01	0,00	0,00	-0,01	0,00	0,01	0,05	1									
19. Div. Payout/Mrkt Cap	0,32	0,02	0,03	0,03	0,00	0,02	-0,07	0,00	0,00	0,00	-0,01	-0,02	-0,03	-0,02	-0,03	-0,01	0,09	0,15	1								
20. Cash Dividends/TA	0,11	0,07	0,03	0,44	0,03	0,64	0,03	0,08	-0,04	0,05	0,03	0,09	0,12	0,07	0,14	0,00	0,05	0,02	0,06	1							
21. Share Rep/TA	0,71	0,00	0,00	-0,06	-0,17	0,00	0,50	0,44	0,06	0,08	0,02	0,11	0,09	0,06	0,07	0,08	0,30	0,07	0,18	0,09	1						
22. Top Owner Holding	0,84	0,01	0,01	-0,02	-0,04	0,00	0,21	0,13	0,03	0,04	0,02	0,04	0,02	0,02	0,01	0,03	0,43	0,25	0,30	0,08	0,21	1					
23. Ceo/Chairman	-0,04	-0,12	-0,06	-0,11	0,05	-0,09	-0,05	-0,01	-0,31	-0,34	-0,21	-0,36	-0,28	-0,20	-0,21	-0,20	-0,03	-0,01	0,00	-0,12	-0,02	-0,05	1				
24. Asset Tangibility	0,02	0,01	0,00	0,27	-0,01	0,19	0,05	0,02	-0,02	0,04	0,06	0,11	0,16	0,10	0,17	0,02	0,02	0,00	0,00	0,15	0,05	0,00	-0,06	1			
25. ROA	-0,05	0,02	0,02	0,06	0,20	0,20	-0,11	0,13	-0,13	-0,13	-0,11	-0,18	-0,24	-0,11	-0,22	-0,15	-0,02	-0,01	0,01	0,05	-0,05	-0,03	0,04	-0,02	1		
26. Yearly Sales Growth	0,31	-0,01	-0,01	-0,05	-0,23	0,00	0,50	0,82	0,02	0,04	0,02	0,08	0,07	0,05	0,05	0,05	0,13	-0,02	-0,01	0,06	0,39	0,12	-0,03	0,03	-0,02	1	
27. Net Income Volatility	-0,03	0,00	0,00	-0,03	0,03	-0,02	0,03	0,04	-0,02	-0,03	-0,03	-0,06	-0,06	-0,04	-0,05	-0,01	-0,01	0,02	-0,02	-0,03	-0,04	-0,01	0,00	-0,02	-0,02	0,08	1

4.1.1 Results

Table 5 reports the results of our baseline analysis.

Table 5 - Fixed effect model regressions – baseline specification

This table reports the estimates obtained using a fixed effect model regression of the payout policy of firm i at time t on common ownership and controls. The dependent variable in this baseline specification is the ratio between the total payout policy of the firm at time t , that is the sum of cash dividend distribution and share buyback, and its total assets. K 5D NAICS is the average of the profit weights (as defined in Section 3.2.1) of firm i at time t with its peers considered at a 5D NAICS level. Size is the natural logarithm of total assets of firm i at time t . Leverage is the ratio of total debt on total assets of firm i at time t . Capex/TA is the ratio between the capital expenditure of the firm i at time t and its total assets. Tobin Q is the proxy of the firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . Asset Tangibility is the ratio between the Net PP&E of firm i at time t and its total asset. ROA is the ratio between the Net Income of firm i at time t and its total assets. Yearly Sales Growth is the proxy of the firm's growth rate and is computed as the ratio between the Total Revenue of firm i at time t and the same variable at time $t-1$. Net Income Volatility is the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$. Block Own, Inst Own, and Block Dummy are three cross-ownership related controls computed as explained in detail in Section 3.2.2. In Columns (1) to (4) I used a fixed effects within estimator. In Column (5). All control variables are winsorized at both 1% and 99% and standardized. Each regression includes a separate intercept. I used a fixed effects first-difference estimator. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. variable	$PayoutPol_{i,t} = \frac{Cash\ Div + Share\ Rep}{Total\ Assets}_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
<i>K</i> 5D NAICS	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.0005)	0.003*** (0.0005)	0.003*** (0.0005)
<i>Size</i>	-0.007 (0.005)	-0.008* (0.005)	-0.007 (0.005)	-0.013** (0.005)	-0.091*** (0.018)
<i>Leverage</i>	-0.005** (0.002)	-0.005** (0.002)	-0.005** (0.002)	-0.004* (0.002)	0.009** (0.004)
<i>Capex/TA</i>	0.0001 (0.001)	9.95e-05 (0.001)	0.0001 (0.001)	-0.0001 (0.001)	0.003** (0.001)
<i>Tobin Q</i>	0.023*** (0.004)	0.022*** (0.004)	0.022*** (0.004)	0.021*** (0.004)	0.007** (0.003)
<i>Asset Tangibility</i>	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.003 (0.004)
<i>ROA</i>	0.014*** (0.003)	0.014*** (0.003)	0.014*** (0.003)	0.014*** (0.003)	0.006*** (0.002)
<i>Yearly Sales Growth</i>	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.003 (0.003)
<i>Net Income Volatility</i>	1.86e-07 (6.45e-07)	2.46e-07 (6.53e-07)	1.47e-07 (6.32e-07)	4.10e-07 (6.83e-07)	9.39e-07 (7.23e-07)
<i>Block Own</i>	0.002 (0.001)			-0.022*** (0.006)	-0.021*** (0.005)
<i>Inst Own</i>		0.004** (0.002)		0.027*** (0.007)	0.023*** (0.006)
<i>Block Dummy</i>			0.002 (0.002)	0.0005 (0.003)	0.007* (0.004)
<i>Constant</i>	0.035*** (0.012)	0.035*** (0.012)	0.034*** (0.011)	0.041*** (0.011)	0.002*** (0.0008)
Observations	21,875	21,875	21,875	21,875	19,781
R-squared	0.445	0.445	0.445	0.447	0.014
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Finally, to address the issue of omitted variables, I estimated a first-differenced (FD) model in Column (5), using the same set of control variables as in Column (4).

The estimator is obtained by running a pooled OLS estimation for a regression of the differenced variables.

In this case, too, the estimated results confirm what I observed in the preceding four columns: a positive and statistically significant coefficient related to the common ownership regressor.

The positive and significant coefficients on K 5-digit NAICS in all five columns of Table 5 suggest that there is a positive and strong relationship between an increase in the level of common ownership and an increase in the remuneration of shareholders in terms of dividend policy.

More specifically, an increase of one standard deviation in the level of K 5-digit NAICS is associated with an increase in the shareholders' remuneration in terms of dividend payout ratio of about 0,3%.

This is an increase of nearly 10% in the overall sample's average payout policy ratio and around 1,2% of its standard deviation.

The estimated coefficients in all the columns are positive and highly significant at the 1% level.

In terms of real economic significance, the estimated coefficient represents an overall average increase in terms of dividends distributed or shares repurchased for each firm of more than € 13 million per year, implying an increase of approximately € 60 billion in the amount of the cash dividend distribution and share repurchases plan if we considered our entire sample.

In reality, as common ownership increases, managers of peer firms compete to provide the highest return for the common investor in order to lower the likelihood of being one of the firms that would be sold if the common investor was afflicted by a negative liquidity shock.

To grow the yield of the shareholders the managers of the firms increase the dividend yield rising the cash dividend distribution or the buyback of its shares.

This effect is robust also using a large number of controls that take into account different aspects of the firm.

Concerning the control variables, we discover that firms with lower levels of leverage, lower sales growth, and higher levels of ROA provide larger remuneration to their shareholders in terms of dividend policy, consistent with the consolidated literature on this topic³⁷.

An interesting result is that associated with the variable *Inst Own_{i,t}*. In both Columns (2) and (4) the coefficient associated with that control variable is positive and significant. This means that an increase in the institutional investors' participation in a firm's ownership is positively correlated with the dividend payout policy of the firm. We will deepen this finding in further detail in section 4.1.3.

4.1.2 Robustness check

In this section, I performed a series of robustness tests of the baseline model. Using the same empirical design and set of control variables in Table 6 we check the robustness of the results obtained in the baseline specification³⁸ using other six measures of common ownership.

In the Column (1) of Table 6 I used profit weights (K) computed at the 4-digit NAICS level. In Columns (2) to (6) I used the other five measures used by He and Huang (2017) as a proxy for the common ownership.

I find that the estimated coefficients are positive and significant in all of the six cases, validating the baseline result both by taking a broader industry definition and by using variables computed with different criteria³⁹.

Table 6 - Robustness checks - 1

This table reports the robustness tests obtained using a fixed effect model regression of the payout policy of firm *i* at time *t* on six different measures of common ownership and the same control variables of the baseline specification. The dependent variable is the same used in the baseline specification, that is the ratio between the total payout policy of the firm at time *t*, the sum of cash dividend distribution and share buyback, and its total assets. K 4D NAICS is the average of the profit weights (as defined in Section 3.2.1) of firm *i* at time *t* with its peers considered at a 4D NAICS level. Num Cross, Num Connected, Cross Dummy, Avg Num, and Total Cross are five measures of common ownership according with He and Huang (2017) defined in Section 3.2.1. Size is the natural logarithm of total assets of firm *i* at time *t*. Leverage is the ratio of total debt on total assets of firm *i* at time *t*. Capex/TA is the ratio between the capital expenditure of the firm *i* at time *t* and its total assets. Tobin Q is the proxy of the firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm *i* at time *t*. Asset Tangibility is the ratio between Net PP&E of firm *i* at time *t* and its total asset. ROA is the ratio between the Net Income of firm *i* at time *t* and its total assets. Yearly Sales Growth is the proxy of firm's growth rate and is computed as the ratio between Total Revenue of firm *i* at time *t* and the same variable at time *t*-1. Net Income Volatility is the average of the standard errors of the residuals of Net Income of firm *i* from time *t* to time *t*-5. Block Own is a

³⁷ see Baker and Powell (2000), for a survey, or Barros et al. (2020) for a more recent work;

³⁸ Column (1) of Table 5;

³⁹ See more detail in Section 3.2.1;

cross-ownership related control computed as explained in detail in Section 3.2.2. In each of the Columns (1) to (6) I used a different measure of common ownership and the same dependent variable. Moreover, I used in all specifications a fixed effects within estimator. All control variables are winsorized at both 1% and 99% and standardized. Each regression includes a separate intercept. I used a fixed effects first-difference estimator. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. variable	Payout Policy _{i,t} = (Cash Div. _{i,t} + Share Rep. _{i,t})/Total Assets _{i,t}					
	(1)	(2)	(3)	(4)	(5)	(6)
K 4D Naics	0.0037* (0.0021)					
Num Cros		0.0043*** (0.0013)				
Num Connected			0.0026** (0.0011)			
Cross Dummy				0.0018* (0.0010)		
Avg Num					0.0022* (0.0011)	
Total Cross						0.00215* (0.00125)
Size	-0.0057 (0.0045)	-0.0104** (0.0040)	-0.0095** (0.0040)	-0.0108** (0.0047)	-0.0113** (0.0047)	-0.00934** (0.00399)
Leverage	-0.0049** (0.0022)	-0.0047** (0.0017)	-0.0047** (0.0017)	-0.0049** (0.0018)	-0.0049** (0.0017)	-0.00490*** (0.00174)
Capex Ratio	0.0003 (0.0010)	0.0016 (0.0015)	0.0016 (0.0015)	0.0028* (0.0015)	0.0027* (0.0015)	0.00143 (0.00150)
Tobin Q	0.0224*** (0.0042)	0.0196*** (0.0032)	0.0197*** (0.0033)	0.4770 (0.4220)	0.4740 (0.4220)	0.0198*** (0.00321)
Asset Tangibility	-0.0011 (0.0019)	-0.0028 (0.0025)	-0.0028 (0.0025)	-0.0036 (0.0024)	-0.0034 (0.0024)	-0.00266 (0.00253)
ROA	0.0139*** (0.0027)	0.0160*** (0.0029)	0.0159*** (0.0029)	0.0192*** (0.0035)	0.0192*** (0.0035)	0.0152*** (0.00278)
Yearly Sales Growth	-0.0059*** (0.0013)	-0.0056*** (0.0001)	-0.0057*** (0.0001)	-0.0053*** (0.0001)	-0.0052*** (0.0010)	-3.231* -1.728
Net Income Volatility	2.79e-07 (6.77e-07)	6.64e-07 (7.47e-07)	6.06e-07 (7.30e-07)	2.56e-07 (7.15e-07)	2.72e-07 (7.02e-07)	6.92e-07 (7.64e-07)
Block Own	0.0016 (0.0012)	-4.85e-05 (0.0013)	0.0010 (0.0013)	0.0010 (0.0012)	0.0001 (0.0012)	0.000493 (0.00110)
Constant	0.0313** (0.0115)	0.0398*** (0.0102)	0.0389*** (0.0103)	0.0557*** (0.0120)	0.0565*** (0.0122)	0.0404*** (0.0100)
Observations	22,554	26,633	26,633	26,633	26,633	26,633
R-squared	0.442	0.405	0.404	0.398	0.398	0.403
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year	Firm & Year

In Table 7, instead, I estimated the baseline specification using three different dependent variables as proxies of the payout policy.

Table 7 - Robustness checks – 2

This table reports the robustness tests obtained using a fixed effect model regression of three different proxies of the dividend payout policy of firm i at time t on the same common ownership and control variables used in the baseline specification. In each of the columns, I used a different dependent variable. In Column (1) I used a ratio between the total payout policy of the firm at time t , the sum of cash dividend distribution and share buyback, and its Book Value of Equity. In Column (2) I used as dependent variable a ratio between the total payout policy of the firm at time t , the sum of cash dividend distribution and share buyback, and its Earnings before extraordinary items. In Column (3) I used as dependent variable a ratio between the total payout policy of the firm i at time t , the sum of cash dividend distribution and share buyback, and its market capitalization. K 5D NAICS is the proxy of common ownership computed as the average of the profit weights (as defined in Section 3.2.1) of firm i at time t with its peers considered at a 5D NAICS level. Size is the natural logarithm of total assets of firm i at time t . Leverage is the ratio of total debt on total assets of firm i at time t . Capex/TA is the ratio between the capital expenditure of the firm i at time t and its total assets. Tobin Q is the proxy of the firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . Asset Tangibility is the ratio between Net PP&E of firm i at time t and its total asset. ROA is the ratio between the Net Income of firm i at time t and its total assets. Yearly Sales Growth is the proxy of firm's growth rate and is computed as the ratio between Total Revenue of firm i at time t and the same variable at time $t-1$. Net Income Volatility is the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$. Block Own is a cross-ownership related control computed as explained in detail in Section 3.2.2. I used in all specifications a fixed effects within estimator. All control variables are winsorized at both 1% and 99% and standardized. Each regression includes a separate intercept. I used a fixed effects first-difference estimator. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variable	<i>Cash Div + Share Rep</i>	<i>Cash Div + Share Rep</i>	<i>Cash Div + Share Rep</i>
	<i>Book Value of Equity</i> _{i,t}	<i>Earnings before extra items</i> _{i,t}	<i>Mrkt Cap</i> _{i,t}
	(1)	(2)	(3)
<i>K 5D Naics</i>	0.009*** (0.002)	0.181*** (0.040)	0.018*** (0.002)
<i>Size</i>	-0.058* (0.031)	-0.158 (0.317)	0.006 (0.006)
<i>Leverage</i>	0.082*** (0.023)	0.188** (0.080)	-6.61e-05 (0.003)
<i>Capex Ratio</i>	-0.0054 (0.004)	-0.144** (0.0584)	-0.0002 (0.0012)
<i>Tobin Q</i>	0.045** (0.016)	-0.099 (0.064)	-0.009*** (0.001)
<i>Asset Tangibility</i>	-0.006 (0.006)	0.003 (0.065)	-0.002 (0.003)
<i>ROA</i>	0.045*** (0.013)	-0.267* (0.140)	0.003 (0.003)
<i>Yearly Sales Growth</i>	-0.011*** (0.003)	0.360 (0.266)	-0.005* (0.003)
<i>Net Income Volatility</i>	-1.65e-06 (3.85e-06)	5.13e-05 (6.41e-05)	-3.54e-08 (1.26e-06)
<i>Block Own</i>	0.013 (0.013)	0.216** (0.079)	0.002 (0.002)
<i>Constant</i>	0.096 (0.085)	1.029 (0.825)	0.033** (0.014)
Observations	21,544	18,322	21,875
R-squared	0.287	0.107	0.268
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
S.E. Cluster	Firm & Year	Firm & Year	Firm & Year

Using profit weights computed at the 5-digit NAICS level (as in the baseline specification) I obtained in all three cases coefficients that are positive and very significant at the 1% level. All the robustness results confirm what we found in the baseline specification. Although the baseline model and the robustness tests produce statistically significant results, my estimates may be influenced by several endogeneity concerns.

For example, a possible reverse causality problem might arise: is it the growth in common ownership that has resulted in a more aggressive payout policy, or is it the high remuneration of the shareholders that has attracted some kind of investor to participate in the company?

Furthermore, even though my analysis includes fixed effects by year and by firm, which help to account for the sample's cross-section and time unobserved heterogeneity, and multiple controls that take into account the most relevant factors that may influence a company's payout policy decision, the estimates may suffer from potential omitted variable problems, which could bias the results obtained.

Therefore, we can only conclude that there is a positive relationship between the rise in common ownership and the firm's payout policy so far.

4.1.3 Further analysis

According to research hypothesis H2, as common ownership grows, management will work to improve shareholder returns by increasing share buyback programs and limiting cash dividend distribution.

This is because a cash dividend payout implies a higher level of market commitment than a share repurchase program. As a result, management will aim to increase shareholder returns more flexibly.

To test this hypothesis, in Columns (1) and (2) of Table 8 I analyze whether the positive relationship found in the baseline specification is due to an increase in cash dividend distribution, share buybacks, or both.

For this analysis, I used the same set of control variables as in the baseline case, as well as the ratio of the firm i 's cash dividends at time t scaled by the total assets of the firm i

at time t in the first column and the ratio of firm i 's share repurchase at time t scaled by total assets of firm i at time t in the second column as dependent variables.

Table 8 – Shareholders remuneration - Cash Dividends vs Share Repurchases program

This table reports the estimates obtained using a fixed effect model regression of two different proxies of the dividend payout policy of firm i at time t on the same common ownership and control variables used in the baseline specification. In the first two columns I used a different dependent variable. In Column (1) I used a ratio between the cash dividends distribution of the firm i at time t , and its total assets. In Column (2) I used a ratio between the share repurchases of the firm i at time t , and its total assets. In Columns (3) and (4) I tested how the presence of the institutional investors in the firm's capital affects the effect of the common ownership on payout policy. K 5D NAICS and K 4D NAICS are the proxies of common ownership computed as the average of the profit weights (as defined in Section 3.2.1) of firm i at time t with its peers considered at a 5D NAICS and 4D NAICS level, respectively. $Inst\ Own$ is the percentage of institutional ownership in firm i at time t . $Size$ is the natural logarithm of total assets of firm i at time t . $Leverage$ is the ratio of total debt on total assets of firm i at time t . $Capex/TA$ is the ratio between the capital expenditure of the firm i at time t and its total assets. $Tobin\ Q$ is the proxy of firm the value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm i at time t . $Asset\ Tangibility$ is the ratio between Net PP&E of firm i at time t and its total asset. ROA is the ratio between the Net Income of firm i at time t and its total assets. $Yearly\ Sales\ Growth$ is the proxy of firm's growth rate and is computed as the ratio between Total Revenue of firm i at time t and the same variable at time $t-1$. $Net\ Income\ Volatility$ is the average of the standard errors of the residuals of Net Income of firm i from time t to time $t-5$. $Block\ Own$ is a cross-ownership related control computed as explained in detail in Section 3.2.2. I used in all specifications a fixed effects within estimator. All control variables are winsorized at both 1% and 99% and standardized. Each regression includes a separate intercept. I used a fixed effects first-difference estimator. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year levels. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. variable	$\frac{Cash\ Div}{Total\ Assets_{i,t}}$	$\frac{Share\ Rep}{Total\ Assets_{i,t}}$	$\frac{Cash\ Div + Share\ Rep}{Total\ Assets_{i,t}}$	
	(1)	(2)	(3)	(4)
<i>K</i> 5-D NAICS	-0.0002** (7.42e-05)	0.002* (0.00118)	-0.0002** (7.71e-05)	
<i>Inst Own</i>			0.008** (0.003)	0.008** (0.003)
<i>Inst Own x K</i> 5-D NAICS			0.016** (0.006)	
<i>K</i> 4-D NAICS				-0.0002* (8.95e-05)
<i>Inst Own x K</i> 4-D NAICS				0.016** (0.006)
<i>Size</i>	-0.019 (0.014)	-0.004 (0.004)	-0.020 (0.014)	-0.019 (0.014)
<i>Leverage</i>	-0.006*** (0.001)	0.005 (0.005)	-0.005*** (0.001)	-0.005*** (0.001)
<i>Capex/TA</i>	0.0006 (0.0006)	-0.001 (0.001)	0.0005 (0.0006)	0.0006 (0.0005)
<i>Tobin Q</i>	0.014*** (0.003)	0.020 (0.016)	0.014*** (0.003)	0.014*** (0.003)
<i>Tangibility</i>	-0.001 (0.002)	-0.002 (0.001)	-0.001 (0.002)	-0.0008 (0.002)
<i>Net Income/TA</i>	0.007*** (0.001)	-0.015 (0.018)	0.007*** (0.001)	0.008*** (0.001)

<i>Yearly Growth Sales</i>	-0.004** (0.001)	-0.003*** (0.001)	-0.004** (0.002)	-0.004** (0.002)
<i>Net Income Volatility</i>	-9.24e-08 (4.14e-07)	4.69e-07 (3.83e-07)	-4.04e-08 (4.25e-07)	1.32e-08 (4.35e-07)
<i>Block Own</i>	0.001 (0.001)	-0.001 (0.002)	-0.006** (0.003)	-0.006** (0.003)
Constant	0.059* (0.030)	0.002 (0.020)	0.061* (0.031)	0.059* (0.030)
Observations	36,792	23,898	36,792	38,095
R-squared	0.281	0.177	0.281	0.282
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
S.E. Cluster	Firm & Year	Firm & Year	Firm & Year	Firm & Year

According to my results, increased common ownership implies a drop in cash dividend distribution and an increase in the company's own share buyback.

The coefficients in Column (1) are indeed negative and statistically significant while the coefficient in Column (2) is positive and statistically significant.

These findings indicate that, in order to maximize the remuneration for their shareholders, managers will opt to raise the buyback of treasury shares at the expense of a lower level of cash dividend distribution. This is an intriguing result since, to the best of my knowledge, my study is the first to demonstrate this association in a common ownership context. This can be explained by the fact that when firm management begins competing against their peers to reduce the risk of the exit threat represented by institutional common shareholders in particular, they prefer to increase shareholder returns by increasing the share value rather than committing to a dividend policy that should not be sustainable for the company in the long term.

Furthermore, by reducing the excess cash flow available to investments, they minimize the asymmetric information with shareholders. Reducing asymmetric information managers creates a virtuous circle for common owners because it lowers their cost of monitoring the assets. In this way, the firm's management obtains a twofold benefit by shielding the company from the probable withdrawal of these investors in the case of a market crisis. This finding is also consistent with that of Semov (2017), who found that a rise in common ownership is associated with reduced cash holdings by firms.

In the last two columns of Table 8, I studied the effect of the common ownership when the presence of institutional investors increases. I carried out this analysis by implementing an interaction variable between the proxy for common ownership, namely the profit weights computed at the 5-digit NAICS level, and the proxy for the presence of institutional investors in the firm's ownership, namely the variable *InstOwn* described in the previous section.

According to the consolidated literature on the effects of institutional investors' common ownership on various firm dynamics⁴⁰, I wanted to show that a greater presence of institutional investors in the firm's capital leads to a greater impact of an increase in common ownership on the firm's payout policy.

The findings provide us with intriguing evidence. The coefficients associated with the *K*'s are negative and statistically significant in both Column (3) (profit weights computed at the 5-digit NAICS) and Column (4) (profit weights computed at the 4-digit NAICS).

As a result, a rise in the level of common ownership in firms with no institutional investors in their capital results in a lower level in the company's dividend payout policy.

However, when we examine both "*Inst Own x K*" interaction coefficients, we notice that the sign of the relation changes. The coefficients in both columns are indeed positive and significant and are greater than the coefficients of only *K*'s (rows 1 and 4 of Table 8). That is, rising the presence of institutional investors in a firm's ownership reverses the negative effect of increasing common ownership on dividend payout policies.

This suggests that the effect shown in our baseline specification is mostly driven by firms that have institutional investors in their capital.

The findings may explain why, as institutional investors' stake in the firm grows, the power of the "exit threat" evolves, having a stronger impact on management's payout policy choice. Indeed, the bigger the percentage of institutional investors, the more the firm's manager will have to compete with more rivals to reduce the risk of an institutional investor withdrawing from her company's capital.

⁴⁰ for more detail see Mancini and Nyeso (2017), Azar et al. (2018), Shy and Stenbacka (2020) and Koch et al. (2021) to learn more about the effects of the common ownership of institutional investors on the competition between peer firms; see Schmalz (2021) for a recent review of the literature about common ownership; see Ramalingegowda et al. (2021) and Wang et al. (2023) to deepen respectively the effect of common ownership of institutional investors on earnings management and the effect on corporate misconduct;

This leads to a stronger focus on shareholders' returns and a more aggressive approach to the payout policy. This is not true when the common owners are non-institutional investors. This is a very interesting result that is in line with the literature about the effects of the common ownership of institutional investors⁴¹. Further, according to H4, in Columns (1) and (2) of Table 9 I investigate whether more common ownership has the same effect in family firms as it does in non-family firms.

Table 9 – Family firms and CEO independence

This table reports the estimates obtained using a fixed effect model regression of the dividend payout policy of firm *i* at time *t* on the same common ownership and control variables used in the baseline specification. However, I divided the sample into two subsamples to analyze the effect of the common ownership in the family firms and the effect of the common ownership when the CEOs are independent in the family firms. In all four columns the dependent variable is the same as the baseline specification. In Column (1) I estimate the effect in the subsample of non-family firms. In Column (2) I estimate the effect in the subsample of family firms. In the last two columns of this table I tested how to change the effect of the common ownership on dividend payout policy in the presence of a dependent CEO (Column 3) or an independent CEO (Column 4) in family firms. *K 5D NAICS* is the proxy of common ownership computed as the average of the profit weights (as defined in Section 3.2.1) of firm *i* at time *t* with its peers considered at a 5D NAICS level. *Size* is the natural logarithm of total assets of firm *i* at time *t*. *Leverage* is the ratio of total debt on total assets of firm *i* at time *t*. *Capex/TA* is the ratio between the capital expenditure of the firm *i* at time *t* and its total assets. *Tobin Q* is the proxy of the firm value computed as the ratio between the sum of Total Assets and Market Value of Equity net of Book Value of Equity on Total Assets of firm *i* at time *t*. *Asset Tangibility* is the ratio between Net PP&E of firm *i* at time *t* and its total asset. *ROA* is the ratio between the Net Income of firm *i* at time *t* and its total assets. *Yearly Sales Growth* is the proxy of firm's growth rate and is computed as the ratio between Total Revenue of firm *i* at time *t* and the same variable at time *t*-1. *Net Income Volatility* is the average of the standard errors of the residuals of Net Income of firm *i* from time *t* to time *t*-5. *Block Own* is a cross-ownership related control computed as explained in detail in Section 3.2.2. I used in all specifications a fixed effects within estimator. All control variables are winsorized at both 1% and 99% and standardized. Each regression includes a separate intercept. I used a fixed effects first-difference estimator. In all the regressions, the standard errors are robust for heteroskedasticity and are clustered both at firm and year level. I report standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Family Firms=0 (1)	Family Firms =1 (2)	Family Firms=1 e CEO/CHAIRMAN =0 (3)	Family Firms =1 e CEO/CHAIRMAN =1 (4)
<i>K 5-D NAICS</i>	0.017* (0.010)	0.003*** (0.0004)	0.002*** (0.0005)	-1.702* (0.840)
<i>Size</i>	-0.012* (0.007)	-0.011 (0.009)	-0.010 (0.008)	-0.058 (0.052)
<i>Leverage</i>	-0.005** (0.002)	-0.001 (0.004)	-0.002 (0.004)	0.016 (0.020)
<i>Capex/TA</i>	0.001 (0.001)	0.0004 (0.002)	0.001 (0.003)	-0.009 (0.011)

⁴¹ See for example Tayachi et al. (2021) in which the authors observe that firms create more profit and improve their dividend payment policies as a result of intensive monitoring by institutional investors since they have access to a large amount of information;

<i>Tobin Q</i>	0.418 (0.421)	0.020** (0.009)	0.012* (0.007)	0.122*** (0.022)
<i>Tangibility</i>	-0.002 (0.002)	-0.005 (0.004)	-0.003 (0.003)	0.020 (0.020)
<i>Net Income/TA</i>	0.020*** (0.004)	0.015*** (0.004)	0.012*** (0.004)	0.105 (0.068)
<i>Y. Growth Sales</i>	-0.006*** (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.009 (0.040)
<i>N.I. Volatility</i>	7.30e-08 (6.67e-07)	7.49e-05 (4.61e-05)	1.27e-05 (5.34e-05)	-2.70e-05 (4.35e-05)
<i>Block Own</i>	0.002* (0.001)	-0.002 (0.003)	-0.001 (0.003)	0.006 (0.014)
Constant	0.061*** (0.019)	0.041** (0.019)	0.045*** (0.015)	0.042 (0.166)
Observations	18,209	2,583	2,465	114
R-squared	0.461	0.326	0.366	0.849
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
S.E. Cluster	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Using data from Orbis (Bureau Van Dijk) I divided the firms in my sample between family firms (if the Global Ultimate Owner is classified as physical persons or family) and non-family firms (if the Global Ultimate Owner is classified with the residuals classifications⁴²). In this way, I detect 813 family firms in my sample. I find that an increase in common ownership has a positive and statistically significant effect on both family and non-family firms' payout policies. In fact, both the coefficients associated with the profit weights computed at the 5-digit NAICS level in Columns (1) and (2) are positive and significant. This means that also in the family firms, the exit threat of the common owners has an effect.

This is most likely due to the family owner's high concentration of interests in the firm in which he is the ultimate owner, as well as a lack of diversification in his investment portfolio, as mentioned above. As a result, the impact on her wealth of a potential decline

⁴² the residuals classifications are insurance company, bank, employees/executives/directors, public authority, sovereign fund, research institute, mutual/retirement fund, hedge fund, finance company, private equity fund, venture capital;

in company value caused by the exit of one or more common owners will be greater than for an investor with a more diversified investment portfolio (for example an investment fund). This suggests an influence in these types of firms as well.

However, this effect seems to be stronger in its magnitude in non-family firms, in which an increase in one standard deviation in the level of common ownership lead to an increase of 1,7% in dividend payout policy, compared to family firms, in which an increase in one standard deviation in the level of common ownership lead to an increase of 0,25% in dividend payout policy despite the low number of observations in the case of family-firms.

Moreover, following the H5, I investigate if this effect is generated by the type of management that drives the firm. Family firms are indeed more probability to have a director coinciding with one of the family members⁴³ (that is, a non-independent director). This is especially true in family-owned firms, when the ultimate owner's stake is quite significant in comparison to the other shareholders. We could expect that common owners' pressure will have less of an effect in such kinds of companies.

Using a dummy variable equal to 1 if the CEO and Chairman of the Board of Directors are the same person and equal to 0 if they are not as a proxy for the CEO's independence from the Board of Directors⁴⁴, in Columns (3) and (4), I find that an increase in the level of common ownership in family firms with an independent CEO (Column (3)) led to a positive effect on dividend payout policy while the effect to family firms in which the CEO overlaps with the chairman of the board of directors (Column (4)) is negative and significant.

This is possible because, as previously said, family firms with independent directors have a more active board than those without. As a result, the corporate governance environment has improved and non-family stakeholders have a stronger effect on managerial choices. Furthermore, the firm's manager will want to avoid having one or more of its significant minority owners exit the company, resulting in a financial loss for the majority shareholders, in order to keep the reputation and trust of family members. This amplifies

⁴³ see Brunninge and Nordqvist (2004);

⁴⁴ If the CEO and the Chairman of the Board of Directors are the same person, it is likely that the CEO will be a member of the family and the Board of Directors will be more passive, according to Burkart et al. (2003);

the "exit threat" for such firms. To the best of our knowledge, this is a novel discovery that contributes to the consolidated literature on family-owned firms.

4.2 Difference in difference approach

As previously discussed, because the estimates generated by fixed effect models may be affected by endogeneity, I used a difference-in-difference technique to try to find a causality explanation for the firms that experimented with an increase in common ownership's more aggressive dividend payout policy.

In this section, following the method used in He and Huang (2017), I address the potential endogeneity issues using a multivariate difference-in-difference approach based on a quasi-natural experiment of financial institution mergers that cause a presumably exogenous change in the level of firms' common ownership⁴⁵.

4.2.1 Setting the Diff-in-Diff

This experiment, initially used by Huang (2013), is based on the idea that financial institution mergers are motivated by factors other than the fundamentals of the stocks they own.

In the United States, for example, a wave of financial mergers occurred following the Gramm-Leach-Bliley Act of 1999, which authorized the merging of commercial banks, investment banks, securities firms, and insurance companies.

Furthermore, previous research shows that corporate strategies such as expanding financial product portfolios or achieving economies of scale are used to encourage mergers between asset management firms Jajaraman et al. (2002).

When two financial institutions merge, the buyer obtains the target's portfolio and usually retains the newly acquired shares for a period of time due to transaction and liquidity expenses (see Holthausen et al. (1990) and Keim and Madhavan (1998)).

As a result, if one of the two merging parties owns stock in a company that operates in an industry and the other owns stock in another company that works in the same industry,

⁴⁵ Azar et al. (2018), Shy and Stenbacka (2020) and Koch et al. (2021), Lewellen and Lowry (2021), Jang et al. (2022) used the same method to address endogeneity problems;

there is no common ownership. However, after the merger the two firms are common owned because they are now owned by the newly merged institution.

Of course, the combined institution may sell the newly acquired shares following the merger for a variety of reasons, including portfolio rebalancing, liquidity needs, portfolio diversification, new industry-specific knowledge, and so on.

However, In the absence of a systemic shock compelling the new corporation to liquidate these cross-shareholdings, I would expect a rise in the level of common ownership for the impacted firms around the merger date.

One distinguishing aspect of this identification approach is that different shocks affect different firms at exogenously different times.

A challenging issue encountered in research using a single shock is the presence of possibly missing factors coinciding with the shock that directly affect the outcome of interest. The identification technique using several shocks helps mitigate this problem.

Because such mergers are exogenous to the common-owned firms, this experiment represents a setting in which changes in common ownership across firms are exogenous to firm investment decisions or dividend payout policy decisions.

4.2.2 Identifying treatment and control firms

Using the SDC's Mergers and Acquisitions database from Refinitiv Eikon, I create a sample of financial institution mergers. The mergers are detected using the criteria provided by He and Huang (2017), with some adjustments.

I require that the merger be announced between 2011 and 2018, between two financial institutions with primary SIC codes ranging from 6000 to 6999.

I also want the merger to be completed within a year of the first announcement. I also need that the acquirer and target's nations to be located in the United States or Europe.

I manually verify the names of each target and acquirer firm involved in these transactions with those provided in Refinitiv Eikon's holdings disclosure. Mergers in which the acquirer or target firm has no ownership in any of the firms in the sample are not included.

This process provides a sample of 69 financial institution mergers, 4 of which meet the criteria for the selection of the treatment firms using the 1% threshold to define blockholdings⁴⁶.

As explained above, according to Banal-Estanol, Boot, and Seldeslachts (2022) we use this threshold as the baseline since 1 percent is arguably the minimum threshold through which owners can have influence. Moreover, this threshold appears to be consistent in a European context where the degree of ownership concentration is higher than in the American context⁴⁷ and the percentage of companies held by cross-owners is lower.

By changing the threshold for the identification of blockholdings from 1% to 0.5% the number of mergers reach 6 while in the absence of any threshold I obtain 10 mergers useful for the experiment.

I identify treatment and control firms following the procedure described in He and Huang (2017). Treatment firms are those in which one of the merging institutions owned a blockholding in the quarter preceding the merger announcement, whereas the other merging party did not own a blockholding but did own at least one industry rival from the same 4-digit NAICS in the same quarter.

Firms controlled by both merging institutions during the quarter preceding the announcement are deleted. Firms that match the selection criteria are included in the treatment sample because they are likely to experience an increase in common ownership linkages with peers in the same industry following the merger event.

This technique produces 45 treatments per year when a 1% threshold is used to define blockholdings, 94 treatments per year when a 0.5% threshold is used, and 1446 treatments per year when no threshold is used.

Control firms are those in which one of the merging institutions holds a blockholding during the quarter preceding the merger announcement, but the other merging party does not. This means that the shared ownership of control businesses will not change solely as a result of the merger, and that treatments and control firms involved in the same merger must be from different industries. The sample consists of 2396 controls per year using a 1% threshold to define blockholdings, 3454 controls per year with a threshold equal to

⁴⁶ see Table II and III of the appendix for more details;

⁴⁷ see Becht and Roell (1999) for additional details;

0.5%, and 8756 controls per year in the absence of any threshold. The above-described selection procedure identifies treatment and control firms based on the merger announced date, so it only relies on ex-ante information, alleviating concerns that the actual cross-holding status of the firm post-merger or its trading decision may be influenced by private information about the firms. I decide to focus on a six-year window around the event year, thus the pre-merger period is defined as the three years preceding the merger, and the post-merger period is defined as the three years after the merger plus the year the merger is completed. Because it spans enough for common owners to influence the company, the event window chosen avoids irrelevant noise for the events while capturing significant changes in the dependent variable in response to exogenous changes in common ownership. To build the DiD sample, I delete observations that are not in either the treatment or control groups. I also exclude any observations that were not included in the six-year window around the event year. The final DiD sample consists of 346 firm-year observations from four institution mergers that used a 1% threshold to define blockholdings, 674 firm-year observations from six institution mergers that used a 0.5% threshold, and 3777 firm-year observations from ten institution mergers that did not use an ownership threshold to identify blockholdings.

4.2.3 *Parallel trend assumption and difference in difference estimation*

Before determining the influence on dividend policy, let's look at the impact of our exogenous shock on the common ownership variable in Table 10.

All else being equal, we expect a merger of two financial institutions to result in an increase in the total level of common ownership, given that the new entity will sell the newly acquired shares following the merger for portfolio rebalancing, liquidity needs, portfolio diversification, and new industry-specific knowledge, but only after a certain amount of time.

According to this, Table 10 shows that mergers of financial institutions result in significant increases in common ownership for the treatments, as evidenced by the positive and significant *Treat x Post* coefficients of the difference in difference regressions using profit weights computed at 5D NAICS (baseline specification) and 4D NAICS as dependent variables, as well as the same set of control variables used in the baseline regression.

Table 10 - Diff-in-diff regressions of Common Ownership around mergers of financial institutions

The table presents the effect of the financial institutions' mergers on common ownership in treatment and control firms. I considered a window of -3 to +3 years around the financial institution mergers' effective date. I used as a dependent variable the profit weights computed at 5D NAICS (baseline) level in Columns (1) to (3) and at 4D NAICS level in Columns (4) to (6) as a proxy of the level of common ownership. *Treat* equals one for Treatment firms and zero for control firms. *Post* is an indicator for years 0 to 3 after the merger. The regressions in Columns (1) and (4) do not include the control variables used in the baseline specification and only the mergers' fixed-effects. The regressions in Columns (2) and (5) include all the control variables used in the baseline specification and only the mergers fixed effects. The regressions in Columns (3) and (6) include all the control variables used in the baseline specification and both the mergers and the years fixed effects. *Treat x Post* is our variable of interest since show us the effect of the mergers of financial institutions of the common ownership of the treated for. Standard errors are robust to heteroscedasticity. I report standard errors in parentheses. All the control variables are winsorized at 1% and 99% and scaled by their respective standard deviations.

Dep. Variable	K 5D NAICS			K 4D NAICS		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Treat x Post</i>	0.078** (0.034)	0.207*** (0.074)	0.293*** (0.080)	0.092*** (0.032)	0.244*** (0.065)	0.293*** (0.080)
<i>Treat</i>	-0.179*** (0.032)	-0.144** (0.070)	-0.214*** (0.074)	-0.211*** (0.030)	-0.210*** (0.061)	-0.214*** (0.074)
<i>Post</i>	-0.126*** (0.016)	-0.212*** (0.030)	-0.084** (0.041)	-0.109*** (0.015)	-0.235*** (0.030)	-0.084** (0.041)
<i>Constant</i>	0.805*** (0.018)	-0.226*** (0.050)	0.148 (0.125)	0.810*** (0.017)	-0.234*** (0.048)	0.148 (0.125)
Observations	25,499	5,948	5,948	26,389	6,132	5,948
Controls	No	Yes	Yes	No	Yes	Yes
R-squared	0.033	0.190	0.197	0.031	0.204	0.197
Merger FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	Yes

Following that, we'll look at how the external shock affected our baseline case's dependent variable, which is the sum of the firm's cash dividends and shares repurchases scaled by total assets at time t .

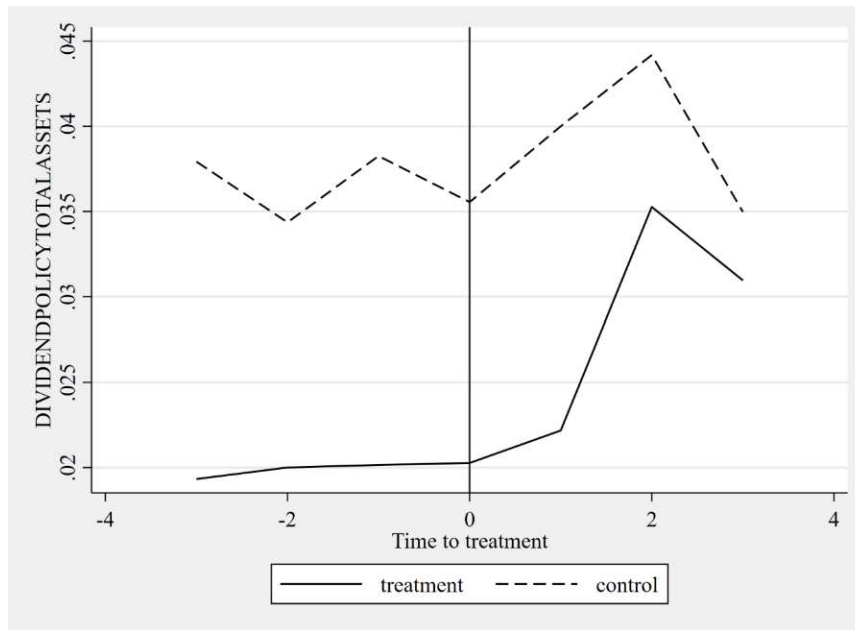
In Figure 2 I illustrate the changes in the dependent variable around the merger.

As you can see from the graph, the horizontal axis indicates the time period relative to the merger ($t=0$). On the vertical axis, there is my dependent variable, the ratio between the firm's payout policy⁴⁸ and its total assets.

⁴⁸ payout policy" refers to the amount of money a firm pays out to its shareholders as dividends or stock buybacks;

Figure 2 – Parallel trend assumption – entire sample

The figure shows the parallel trends between treatment and control firms' payout policies before the financial institutions' mergers and their different reactions post mergers when considering all the firms in the sample. Treatment and control firms are described in Section 4.3.2. I used a threshold of 1% for identifying treatment firms.



Although controls are increasing post-merger, the growth of dividend payout policies after the merger in treated firms is certainly more pronounced. This is supported by the positive and significant coefficient of the *Treat x Post* variable in Columns (1) to (3) of Table 11.

This result appears to support the findings of Di Giuli et al. (2021).

Using data from 193 Sweden firms they found that dividend policies of firms newly added to a common owners' portfolio evolve towards the dividend policies of the existing firms in this portfolio.

Table 11 - Diff-in-diff regressions of Payout Policy around mergers of financial institutions – all sample

The table presents the effect of the financial institutions' mergers on the payout policy in treatment and control firms using all the firms in my sample. I considered a window of -3 to +3 years around the financial institution merger effective date. In Columns (1) to (3) I used as dependent variable the ratio between the total payout policy of the firm at time *t*, the sum of cash dividend distribution and share buyback, and its total assets while in Columns (4) to (6) I used as dependent variable that is the ratio between the total payout policy of the firm at time *t*, the sum of cash dividend distribution and share buyback, and its market capitalization. *Treat* equals one for Treatment firms and zero for control firms. *Post* is an indicator for years 0 to 3 after the merger. The regressions in columns (1) and (4) not include the control variables used in the baseline specification and only the mergers fixed effects. The regressions in Columns (2) and (5) include all the control variables used in the baseline specification and only the mergers fixed effects. The regressions in Columns (3) and (6) include all the control variables used in the baseline specification and both the mergers and the years fixed effects. *Treat x Post* is our variable of interest since show us the effect of the mergers of

financial institutions of the common ownership of the treated for. Standard errors are robust to heteroscedasticity. I report standard errors in parentheses. All the control variables are winsorized at 1% and 99% and scaled by their respective standard deviations.

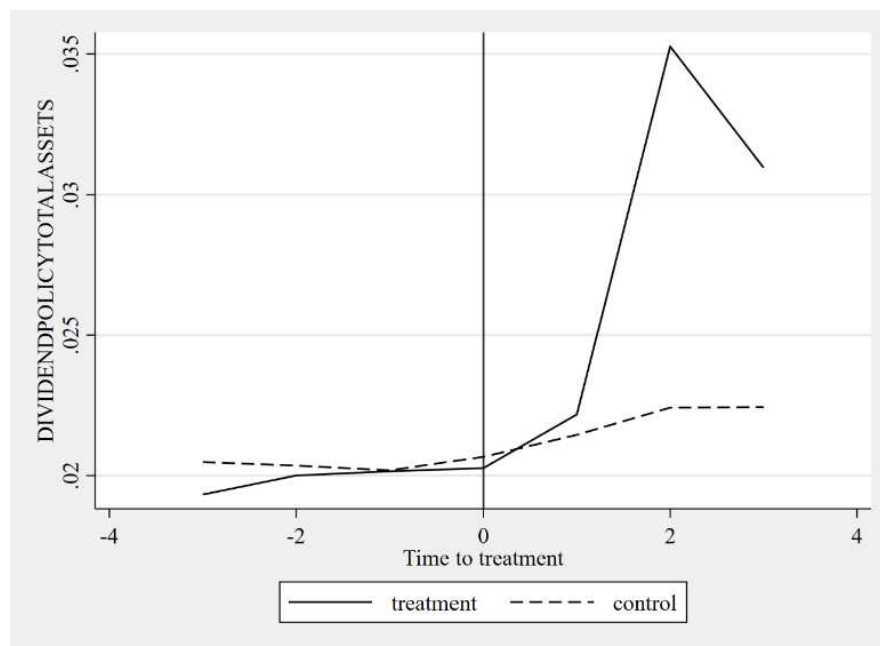
Dep. Variable	Payout Policy/Total Assets			Payout Policy/Mrkt Cap		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Treat x Post</i>	0.018*** (0.004)	0.009* (0.005)	0.010* (0.006)	0.072** (0.032)	0.065** (0.033)	0.071** (0.035)
<i>Treat</i>	-0.011*** (0.003)	-0.013*** (0.005)	-0.014*** (0.005)	-0.095** (0.037)	-0.083** (0.037)	-0.088** (0.038)
<i>Post</i>	-0.003 (0.003)	-0.002 (0.002)	0.002 (0.003)	-0.015 (0.011)	-0.013** (0.005)	-0.013 (0.011)
<i>Size</i>		-0.001 (0.001)	-0.001 (0.001)		0.005** (0.003)	0.005** (0.002)
<i>Leverage</i>		-0.001 (0.001)	-0.001 (0.001)		-0.006* (0.003)	-0.007** (0.003)
<i>Capex/TA</i>		0.004*** (0.001)	0.005*** (0.001)		0.001 (0.002)	0.003 (0.002)
<i>Tobin Q</i>		0.021*** (0.002)	0.022*** (0.002)		-0.010*** (0.002)	-0.009*** (0.002)
<i>Asset Tangibility</i>		0.007 (0.001)	0.001 (0.001)		0.003 (0.002)	0.004* (0.002)
<i>ROA</i>		0.017*** (0.002)	0.017*** (0.002)		0.007* (0.004)	0.007* (0.004)
<i>Y. Growth Sales</i>		-0.008*** (0.001)	-0.008*** (0.001)		-0.011*** (0.002)	-0.010*** (0.002)
<i>N.I. Volatility</i>		3.69e- 06*** (1.15e-06)	3.88e- 06*** (1.13e-06)		1.20e-06 (1.68e-06)	1.53e-06 (1.75e-06)
<i>Block Own</i>		0.002** (0.001)	0.002** (0.001)		-0.001 (0.002)	-0.001 (0.003)
<i>Constant</i>	0.036*** (0.003)	0.013*** (0.005)	0.012* (0.007)	0.050*** (0.007)	0.061*** (0.008)	0.080*** (0.023)
Observations	4,758	4,421	4,421	4,740	4,423	4,423
R-squared	0.022	0.203	0.216	0.108	0.145	0.160
Merger FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	No	Yes
S.Errors	Robust	Robust	Robust	Robust	Robust	Robust

This means that an higher level of common ownership leads to greater convergence of dividend policy among the firms in the common owner's portfolio. My conclusion points in this direction and holds true even when utilizing a different approach and a larger European sample.

Furthermore, in Columns (4) to (6) I also employ a different proxy for the payout ratio as a measure of the baseline regression's robustness (that is the ratio between the payout policy on market capitalization). This interpretation is true if we focus on all control firms in our sample. However, in Figure 3 we examine the effect of the shock on the treated and on a subsample of control firms that had, on average, the same dividend payout policy as the treated before the merger.

Figure 3 Parallel trend assumption – only similar firms' subsample

The figure shows the parallel trends between treatment and control firms' payout policies before the financial institutions' mergers and their different reactions post mergers when considering only the firms with similar payout policies before the mergers. Treatment and control firms are described in Section 4.1.2. I used a threshold of 1% for identifying treatment firms.



We see that the effect of the shock on the treated firms is positive and significant both graphically and statistically (see estimates results in Table 12 with two different dependent variables).

In this scenario, whereas the dividend payout policy of the control firms is more or less flat both before and after the shock, the dividend payout policy of the treatment firms is clearly increasing.

This reveals that a higher level of common ownership actually causes in the treatment firms a significant increase in remuneration to shareholders in terms of dividend payout policy when compared to “similar⁴⁹” control firms.

Moreover, this last result also suggests a convergence of the dividend payout policies of the firms treated with those of the companies already in the portfolio of common shareholders.

Furthermore, the post-treatment rise appears to be slightly delayed in time. In reality, the increase in treatment firms happens especially in the second period.

This makes sense given that the firms' dividend payout policy has been steady throughout time.

As a result, it will take time for common owners to exert influence on the management of common owned firms to obtain a more aggressive dividend payout policy. Furthermore, unlike the previous literature, we used the year of the merger as year 0 in the difference-in-difference approach.

However, the consequences of the merger had not yet fully revealed themselves that year. As a result, the final effect on our dependent variable is one period delayed. These findings, in my opinion, are quite fascinating since they corroborate and expand on previous findings in the literature using a new and broader European dataset. Furthermore, our findings fill a gap in the literature on common ownership and its implications on firm-level dividend payout policy decisions.

Table 12 Differences-in-differences regressions of Payout Policy around mergers of financial institutions – similar firms’ subsample

The table presents the effect of the financial institutions’ mergers on the payout policy in treatment and control firms using only the firms that pre-merger had a similar dividend payout policy. I considered a window of -3 to +3 years around the financial institution merger effective date. In all the columns I used as dependent variable the ratio between the total payout policy of the firm at time t , the sum of cash dividend distribution and share buyback, and its total assets. *Treat* equals one for Treatment firms and zero for control firms. *Post* is an indicator for years 0 to 3 after the merger. The regression in Column (1) does not include the control variables used in the baseline specification but include both the mergers and the years fixed effects. The regression in Column (2) includes all the control variables used in the baseline specification and only the mergers fixed effects. The regressions in Column (3) includes all the control variables used in the baseline specification and both the mergers and the years fixed effects. *Treat x Post* is our variable of interest since show us the effect of the mergers of financial institutions of the common ownership of the treated for.

⁴⁹ In the sense that, before to treatment, they had very comparable dividend payout policies;

Standard errors are robust to heteroskedasticity. I report standard errors in parentheses. All the control variables are winsorized at 1% and 99% and scaled by their respective standard deviations.

Dep. variable	<i>Payout Pol</i>		
		<i>TA</i>	
	(1)	(2)	(3)
<i>Treat x Post</i>	0.012*** (0.003)	0.009** (0.004)	0.008** (0.004)
<i>Treat</i>	0.003 (0.003)	0.001 (0.003)	0.002 (0.003)
<i>Post</i>	4.22e-05 (0.001)	0.002** (0.001)	0.002* (0.001)
<i>Constant</i>	0.022*** (0.001)	0.013*** (0.003)	0.012*** (0.003)
Observations	4,102	3,786	3,786
R-squared	0.055	0.157	0.176
Controls	No	Yes	Yes
Merger FE	Yes	Yes	Yes
Year FE	Yes	No	Yes
St. Errors	Robust	Robust	Robust

4.2.4 Robustness checks

One possible issue with the difference in difference approach explained in section 4.1 is the adoption of a 1% threshold for identifying between treated and control firms. This is because, according to Banal estanol et al., 1% is the minimum necessary with which an owner may influence the company's strategic decisions.

As a result, as previously stated, a treatment firm was only recognized if both entities participating in the merger held at least 1% of the same firm before the merger.

However, after evaluating the ownership structure of the firms in our dataset, I found that the average cross-owners' ownership in the European setting is just under 0,5% (exactly 0,45%).

As a result, utilizing the 1% threshold, whereas more significant in terms of understanding the phenomena, implies fewer treatment and control firms. For these reasons, I conduct a robustness check of the Diff-in-Diff approach used in section 4.1 using a threshold of 0,5% for identifying treatment firms.

In this way, I obtained a double number of treatment firms (94 vs 45 in the 1% case) and more control firms (3454 vs 2396 in the 1% case).

Following the same step used in the section before I first verified the impact of the mergers on the variable of common ownership.

The coefficients associated with the variable *Treat x Post* in all columns of Table 13 are positive and statistically significant.

It indicates that around mergers, treatment firms experience a positive and significantly greater growth in the level of common ownership than control firms.

This impact is true whether profit weights are computed at the 5D or 4D NAICS levels and considering only merger fixed-effects or both merger and year fixed-effects. The controls used are the same as those defined in the baseline specification.

Table 13 - Differences-in-differences regressions of Common Ownership around mergers of financial institutions – robustness check

The table presents the effect of the financial institutions' mergers on common ownership in treatment and control firms using a threshold for identifying treatments at 0,5%. I considered a window of -3 to +3 years around the financial institution merger effective date. I used as a dependent variable the profit weights computed at 5D NAICS (baseline) level in Columns (1) and (2) and 4D NAICS level in Columns (3) and (4) as a proxy of the level of common ownership. *Treat* equals one for Treatment firms and zero for control firms. *Post* is an indicator for years 0 to 3 after the merger. The regressions in Columns (1) and (3) include all the control variables used in the baseline specification and only merger fixed effects. The regressions in Columns (2) and (4) include all the control variables used in the baseline specification and both merger and year fixed effects. *Treat x Post* is our variable of interest since show us the effect of the mergers of financial institutions of the common ownership of the treated for. Standard errors are robust to heteroskedasticity. I report standard errors in parentheses. All the control variables are winsorized at 1% and 99% and scaled by their respective standard deviations.

Dep. variable	K 5D NAICS		K 4D NAICS	
	(1)	(2)	(3)	(4)
<i>Treat x Post</i>	0.140** (0.065)	0.208*** (0.069)	0.134** (0.066)	0.208*** (0.069)
<i>Treat</i>	-0.147** (0.061)	-0.205*** (0.063)	-0.198*** (0.060)	-0.205*** (0.063)
<i>Post</i>	-0.161*** (0.023)	-0.020 (0.031)	-0.176*** (0.022)	-0.020 (0.031)
<i>Constant</i>	-0.432*** (0.038)	-0.149* (0.080)	-0.486*** (0.038)	-0.149* (0.080)
Observations	11,512	11,512	11,936	11,512

Controls	Yes	Yes	Yes	Yes
R-squared	0.155	0.161	0.171	0.161
Merger FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
St. Errors	Robust	Robust	Robust	Robust

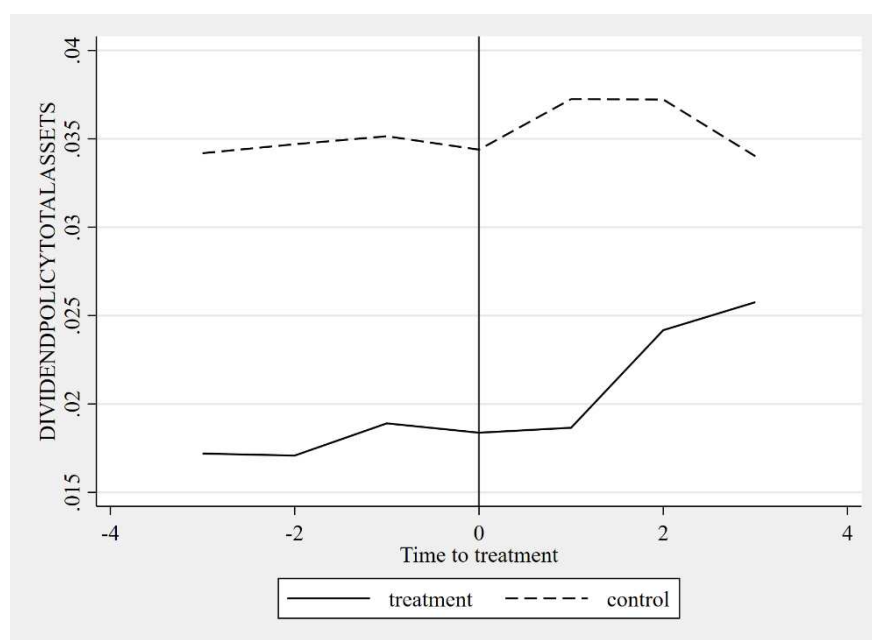
Next, as in the previous section, by observing Figure 4 it can be seen the changes in the dependent variable after the merger.

We can observe that there is evidence of differential responses to events for the treatment firms as compared to the control firms' flatter path.

Moreover, using the same multivariate difference in difference setting used in the previous section and two different dependent variables, I obtained in Table 14 that all the coefficients associated with the variable Treat x Post are positive and statistically significant.

Figure 4 – Parallel trend assumption – robustness with entire sample

The figure shows the parallel trends between treatment and control firms' payout policies before the financial institutions' mergers and their different reactions post mergers when considering all the firms in the sample. Treatment and control firms are described in Section 4.1.2. I used a threshold of 0,5% for identifying treatment firms.



Finally, in Figure 5 and Table 15, I examine the impact of an exogenous shock on the dividend payout policies of treatment firms and their "similar" control firms.

Both graphically (see Figure 5) and statistically (see *Treat x Post* coefficients in Table 15), the result is quite evident.

Table 14 - Differences-in-differences regressions of Payout Policy around mergers of financial institutions – robustness check with entire sample

The table presents the effect of the financial institutions' mergers on the payout policies in treatment and control firms using a threshold for identifying treatments at 0,5%. In these regressions, I used all the firms in my sample. I considered a window of -3 to +3 years around the financial institution merger effective date. In Columns (1) and (2) I used as dependent variable the ratio between the total payout policy of the firm at time t , the sum of cash dividend distribution and share buyback, and its total assets while in Columns (3) and (4) I used as dependent variable that is the ratio between the total payout policy of the firm at time t , the sum of cash dividend distribution and share buyback, and its market capitalization. *Treat* equals one for Treatment firms and zero for control firms. *Post* is an indicator for years 0 to 3 after the merger. The regressions in Columns (1) and (3) not include the control variables used in the baseline specification but include both the mergers and years fixed effects. The regressions in Columns (2) and (4) include all the control variables used in the baseline specification and both the mergers and years fixed effects. *Treat x Post* is our variable of interest since show us the effect of the mergers of financial institutions of the common ownership of the treated for. Standard errors are robust to heteroskedasticity. I report standard errors in parentheses. All the control variables are winsorized at 1% and 99% and scaled by their respective standard deviations.

Dep. variable	<i>Cash Div + Share Rep</i> <i>TA</i> <i>i,t</i>		<i>Cash Div + Share Rep</i> <i>Mrkt Cap</i> <i>i,t</i>	
	(1)	(2)	(3)	(4)
<i>Treat x Post</i>	0.014*** (0.003)	0.015*** (0.004)	0.028*** (0.010)	0.023** (0.010)
<i>Treat</i>	-0.013*** (0.003)	-0.021*** (0.004)	-0.043*** (0.012)	-0.034*** (0.012)
<i>Post</i>	-0.007*** (0.002)	-0.005** (0.002)	-0.010* (0.006)	-0.010* (0.006)
<i>Constant</i>	0.033*** (0.003)	-0.0004 (0.004)	0.043*** (0.003)	0.058*** (0.013)
Observations	9,763	9,153	9,729	9,155
R-squared	0.021	0.232	0.064	0.085

Controls	No	Yes	No	Yes
Merger FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
St. Errors	Robust	Robust	Robust	Robust

According to the results obtained in section 4.1.3, robustness results obtained using a 0.5% threshold to identify treatments and controls reveal that an increase in the level of common ownership causes a significant increase in dividend payout policy in the treatment firms when compared to their "similar" control firms.

Furthermore, when I compare the effect using all of the firms in the sample, the increase in treatment firms is positive and statistically significant, but graphically it suggests a convergence of the dividend payout policies of the firms treated with those of the companies already in the portfolio of common shareholders, which is consistent with the findings of Di Giuli et al. (2021). These results fully support the conclusions outlined in section 4.1.3.

Figure 5 – Parallel trend assumption – robustness with only similar firms’ subsample

The figure shows the parallel trends between treatment and control firms’ payout policies before the financial institutions’ mergers and their different reactions post mergers when considering only the firms with similar payout policies before the mergers. Treatment and control firms are described in Section 4.1.2. I used a threshold of 0,5% for identifying treatment firms.

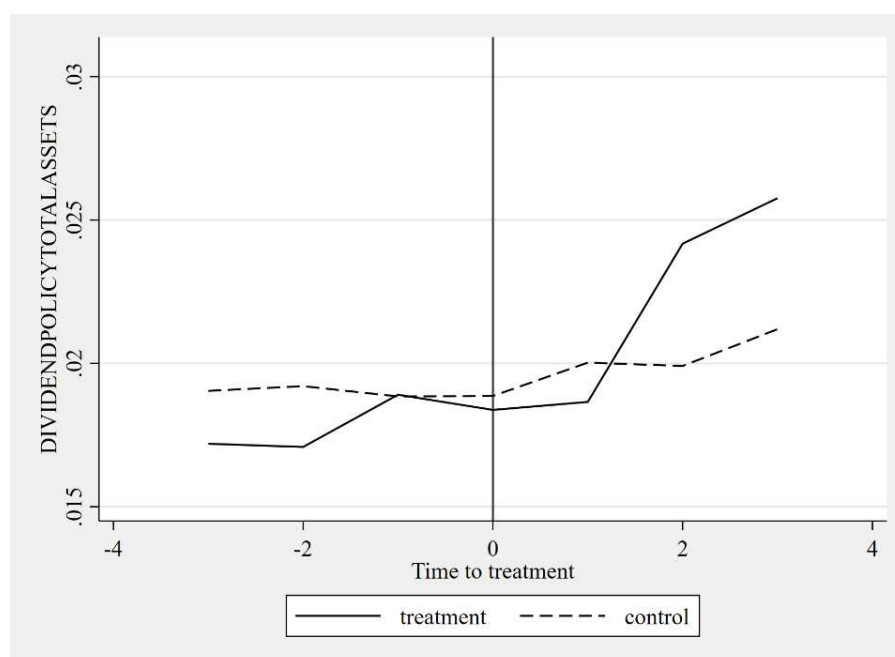


Table 15 - Differences-in-differences regressions of Payout Policy around mergers of financial institutions – robustness with similar firms’ subsample

The table presents the effect of the financial institutions’ mergers on the payout policy in treatment and control firms using a threshold for identifying treatments at 0,5%. In these regressions, I used only the firms with a similar dividend payout policy before the mergers. I considered a window of -3 to +3 years around the financial institution merger effective date. In all the columns I used as dependent variable the ratio between the total payout policy of the firm at time t , the sum of cash dividend distribution and share buyback, and its total assets. *Treat* equals one for Treatment firms and zero for control firms. *Post* is an indicator for years 0 to 3 after the merger. The regression in Column (1) does not include the control variables used in the baseline specification but include both the mergers and the years fixed effects. The regression in Columns (2) includes all the control variables used in the baseline specification and only the mergers fixed effects. The regressions in Columns (3) includes all the control variables used in the baseline specification and both the mergers and the years fixed effects. *Treat x Post* is our variable of interest since show us the effect of the mergers of financial institutions of the common ownership of the treated for. Standard errors are robust to heteroskedasticity. All the control variables are winsorized at 1% and 99% and scaled by their respective standard deviations.

VARIABLES	<i>Payout Pol</i> <i>TA</i>		
	(1)	(2)	(3)
<i>Treat x Post</i>	0.0120*** (0.00337)	0.00868** (0.00368)	0.00831** (0.00375)
<i>Treat</i>	0.00329 (0.00272)	0.00127 (0.00306)	0.00146 (0.00312)
<i>Post</i>	4.22e-05 (0.00128)	0.00157** (0.000614)	0.00207* (0.00123)
<i>Constant</i>	0.0218*** (0.00142)	0.0133*** (0.00250)	0.0119*** (0.00296)
Observations	4,102	3,786	3,786
R-squared	0.055	0.157	0.176
Controls	No	Yes	Yes
Merger FE	Yes	Yes	Yes
Year FE	Yes	No	Yes
St. Errors	Robust	Robust	Robust

5. Conclusions

In my research, I investigate how common ownership affects a firm's payout policy using a dataset of 4595 European firms. Computing common ownership measures at the across-industry 3-D, 4-D, and 5-D NAICS level and using a multivariate fixed effect model I found that an increase in the degree of common ownership is associated with a firm’s more aggressive payout policy caused by the “exit threat” of the common investors.

This effect is robust to alternative specifications that use different proxies for the payout policy and the level of common ownership.

Furthermore, and intriguingly, I found that this effect is driven by an increase in the firms' share repurchase program and by the institutional investors' common owners, according to Fichtner (2020).

The increased payout policy, in fact, should lower the likelihood of an exit by one or more common owners (in my framework with at least 1% ownership of the firm) in the event of a negative liquidity shock. Furthermore, the firm's management obtains an indirect effect of intensifying the monitoring channel reducing the agency costs between management and shareholders.

This result is also in line with that found by Semov (2017) who found that an increase in common ownership is positively associated with a lower level of cash holdings.

I tried to look for causality using a difference-in-differences approach based on the quasi-natural experiment of the financial institutions following He and Huang (2017).

Using a 1% threshold to identify treated and control firms, I proved that an increase in common ownership causes a significant increase in dividend payout policy in treatment firms when compared to "similar" control firms.

Furthermore, when I compare the effect using all the firms in the sample, the rise in treatment firms is positive and statistically significant, and graphically it suggests a convergence of the dividend payout policies of the firms treated with those of the companies already in common shareholders' portfolios. This finding is consistent with that of Di Giuli et al. (2021).

Finally, to address the gap in the literature regarding the connection between common ownership and family firms, I investigated this relation founding that the effect of an increase in common ownership on payout policy is still positive and statistically significant in family firms.

However, this effect is driven by the governance structure of the firm, rather than the type of firm. Specifically, family firms with an independent CEO exhibit a positive effect, while those with a CEO who also serves as the chairman of the board of directors show a negative and significant effect.

To our knowledge, this is a novel finding that adds to the consolidated literature on family firms and common ownership.

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Appendix

Table I - Definition of the variables

Variable	Definition	Source
<i>K</i>	the profit weights computed according to Azar (2012). See section 3.2.1.	Refinitiv Eikon
<i>Cross Dummy</i>	a dummy variable that is equal to 1 if the firm is cross-held by at least one investor in any of the four quarters in a fiscal year	Refinitiv Eikon
<i>Num Connected</i>	the number of same-industry peers that share any common blockholder with the firm in a given quarter	Refinitiv Eikon
<i>Num Cross</i>	the number of unique blockholders that cross-hold the firm in a given quarter	Refinitiv Eikon
<i>Avg Num</i>	the number of same industry peers block-held by each cross-holding investor in a given quarter	Refinitiv Eikon
<i>Total Cross Own</i>	the sum of the ownership shares of each cross-holding institution in a given firm for the quarter	Refinitiv Eikon
<i>Block Own</i>	the sum of institutional blockholders' ownership shares in the firm for the quarter and I averaged across the four quarters of a fiscal year	Refinitiv Eikon
<i>Inst Own</i>	the average among the four quarters of a fiscal year of the percentage ownership by institutional investors in a given firm	Refinitiv Eikon
<i>Block Dummy</i>	a dummy variable equal to 1 if the firm is blockheld by at least one institutional investor in any of the four quarters in a fiscal year	Refinitiv Eikon
<i>Size</i>	the logarithm of the book value of assets in year t	Refinitiv Eikon
<i>Leverage</i>	the ratio between the long-term debt and the total assets of the firm in year t	Refinitiv Eikon
<i>Capex Ratio</i>	the ratio between the capex and the total assets of the firm in year t	Refinitiv Eikon
<i>Tobin Q</i>	the ratio between the sum of the book value of assets plus the market value of equity minus the book value of equity of the firm in year t and the book value of equity of the firm in year t	Refinitiv Eikon
<i>Tangibility</i>	the ratio of Net PP&E on Total Assets at time t	Refinitiv Eikon
<i>ROA</i>	the ratio between Net Income and Total Asset at time t	Refinitiv Eikon
<i>Yearly Sales Growth</i>	the ratio between total revenue of the firm in year t and t-1	Refinitiv Eikon
<i>Net Income Volatility</i>	the average of the standard errors of the residuals of Net Income of firm i from time t to time t-5	Refinitiv Eikon
<i>Dividend Payout</i>	sum of firm's cash dividends and share repurchases at time t	Refinitiv Eikon
<i>Dividend Payout/TA</i>	sum of firm's cash dividends and share repurchases scaled by total assets at time t	Refinitiv Eikon
<i>Dividend Payout/Mrkt Cap</i>	sum of firm's cash dividends and share repurchases scaled by market capitalization at time t	Refinitiv Eikon
<i>Dividend Payout/Net Income</i>	sum of firm's cash dividends and share repurchases scaled by Net Income at time t	Refinitiv Eikon
<i>Dividend Payout/BV of Equity</i>	sum of firm's cash dividends and share repurchases scaled by Book Value of Equity at time t	Refinitiv Eikon
<i>Share Repurchases/TA</i>	the ratio between the firm's share repurchases and total assets at time t	Refinitiv Eikon
<i>Cash Dividends/TA</i>	the ratio between the firm's cash dividends and total assets at time t	Refinitiv Eikon

Table II - All Mergers considered in Difference in Difference approach

Acquiror Name	Target Name	Date Announced	Number Of Days	Date Effective
AXA Group	Sanford C. Bernstein & Co., L.L.C.	20/06/2000	104	02/10/2000
SHV Holdings N.V.	NPM Capital (Nederlandse Participatie Maatschappij) N.V.	14/07/2000	105	27/10/2000
Chase Manhattan Ahorro S.G.I.I.C., S.A._NLE	JP Morgan	13/09/2000	109	31/12/2000
Allianz	Nicholas-Applegate Capital Management, LLC_NLE	18/10/2000	119	14/02/2001
Franklin Templeton Investments Corporation	Fiduciary Trust Co International of Pennsylvania	25/10/2000	167	10/04/2001
United International Enterprises Ltd	International Plantations & Finance	24/04/2002	65	28/06/2002
Panther Securities P L C	Eurocity Properties PLC	08/11/2002	89	05/02/2003
Banc One Investment Advisors/Detroit_NLE	Security Capital Research & Management, Inc.	16/09/2003	71	26/11/2003
Bank of America Corp	Fleet Boston Financial_NLE	27/10/2003	157	01/04/2004
AXA Group	Finaxa SA	19/04/2005	241	16/12/2005
IFG Trust (Jersey) Ltd.	Bank of Scotland Trust Company (International) Ltd	28/12/2005	0	28/12/2005
Mattioli Woods PLC	Suffolk Life Trustee Company Limited	30/01/2006	0	30/01/2006
Blackrock	Merrill Lynch Investment Managers_NLE	15/02/2006	226	29/09/2006
Snefonn AS	Havfonn AS	21/03/2006	0	21/03/2006
La Gaiana SpA	Gabetti Property Solutions SpA	16/10/2006	193	27/04/2007
MorganStanley_aggregate	FrontPoint Partners LLC_NLE	31/10/2006	34	04/12/2006
Bank of New York (Sibling)	Mellon Bank, N.A._NLE	03/12/2006	211	02/07/2007
Baugur Group hf	Immo Croissance SICAV-FIS	27/06/2007	225	07/02/2008
AXA Group	Nationale Suisse Assurances_NLE	23/07/2007	67	28/09/2007
Lehman Brothers Holdings Inc	David J. Greene and Company, LLC_NLE	23/04/2008	160	30/09/2008
Bank of America Corp	Merrill Lynch & Company, Inc._NLE	14/09/2008	109	01/01/2009
Barclays Bank PLC	Lehman Brothers Inc._NLE	16/09/2008	6	22/09/2008
HBK Invest AS	BSB Invest AS_NLE	02/01/2009	0	02/01/2009
Skagenkaien Eiendom AS	Biovekst AS	01/02/2009	0	01/02/2009
Blackrock	Barclays Global Investors Japan Ltd._NLE	11/06/2009	173	01/12/2009
Astaire Group Ltd	Ruegg & Co Ltd	23/07/2009	0	23/07/2009
Blackrock	Barclays Global Investors Ltd	16/09/2009	76	01/12/2009
Bure Equity AB	Skanditek Industriforvaltning AB	14/10/2009	105	27/01/2010
Evli Pankki Oyj	Erik Penser Fonder AB_NLE	20/10/2009	106	03/02/2010
Aviva Investors Global Services Limited	River Road Asset Management, LLC	05/01/2010	58	04/03/2010
Affiliated Managers Group Inc	Artemis Investment Management LLP	01/02/2010	42	15/03/2010
Goldman Sachs	Level Global Investors, L.P._NLE	06/04/2010	0	06/04/2010

Man Group PLC	GLG Partners Inc.	17/05/2010	150	14/10/2010
GLI Finance, Ltd.	Asset Management Investment Company Ltd	26/10/2010	98	01/02/2011
AcomeA SGR S.p.A.	Leonardo SGR S.p.A._NLE	31/01/2011	150	30/06/2011
Bryn Mawr Trust Company	Private Wealth Management	21/02/2011	95	27/05/2011
Yorkshire Building Society	Norwich & Peterborough Building Society	18/03/2011	230	03/11/2011
Ziegler Capital Management, LLC	Lotsoff Capital Management_NLE	28/04/2011	43	10/06/2011
KBC Asset Management N.V.	KBC Towarzystwo Funduszy Inwestycyjnych S.A.	17/01/2012	155	20/06/2012
Talanx AG	Towarzystwo Ubezpieczen i Reasekuracji Warta SA	20/01/2012	163	01/07/2012
James Hambro & Partners LLP	Calkin Pattinson & Co. Ltd._NLE	16/08/2012	0	16/08/2012
Cassa Depositi e Prestiti, S.p.A.	Fintecna S.p.A.	24/10/2012	16	09/11/2012
Lone Star Funds	TLG IMMOBILIEN AG	12/12/2012	0	12/12/2012
Peoples Financial Services Corp.	Penseco Financial Services Corp._NLE	28/06/2013	157	02/12/2013
Miton Group Ltd	PSigma Asset Management Holdings Limited_NLE	02/07/2013	1	03/07/2013
Ader Investment Management LLC_NLE	Springowl Associates LLC	23/10/2013	0	23/10/2013
Vienna Insurance Group AG Wiener Versicherung Gruppe	AXA Group	23/12/2013	165	06/06/2014
Affiliated Managers Group Inc	River Road Asset Management, LLC	28/03/2014	94	30/06/2014
Ingenious Asset Management Limited_NLE	Thurleigh Investment Managers LLP_NLE	03/04/2014	133	14/08/2014
Man Group PLC	Numeric Investors LLC	19/06/2014	78	05/09/2014
The Blackstone Group	Lombard International Assurance, S.A.	11/07/2014	112	31/10/2014
Hunters Group Ltd.	Hunters Property Group Ltd	31/07/2014	0	31/07/2014
Aviva PLC	Friends Life Group Ltd	21/11/2014	140	10/04/2015
Ziegler Capital Management, LLC	Fiduciary Asset Management, LLC_NLE	29/05/2015	0	29/05/2015
KCI SA	Gremi Media SA	02/10/2015	221	10/05/2016
Allianz	Rogge Global Partners Limited_NLE	08/02/2016	114	01/06/2016
Boston Financial Management LLC	Emerson Investment Management LLC_NLE	02/05/2016	0	02/05/2016
Advisory Research, Inc.	Cupps Capital Management, LLC_NLE	18/08/2016	1	19/08/2016
NN Group N.V.	Delta Lloyd NV	05/10/2016	239	01/06/2017
Aspiriant, LLC	Stanford Investment Group Inc._NLE	12/12/2016	51	01/02/2017
Liontrust Asset Management PLC	Alliance Trust Investments Limited_NLE	14/12/2016	110	03/04/2017
Eiffel Investment Group S.A.S.	Alto Invest	02/03/2017	0	02/03/2017
IP Group PLC	Touchstone Innovations Ltd	23/05/2017	199	08/12/2017
RMB Capital Management, LLC	Jacobus Wealth Management, Inc._NLE	26/10/2017	66	31/12/2017
SEI Investments Company	Huntington Steele LLC_NLE	02/04/2018	0	02/04/2018
Schonfeld Strategic Advisors LLC	Folger Hill Asset Management LLC_NLE	10/04/2018	0	10/04/2018
Seven Investment Management LLP	Tcam Asset Management Limited_NLE	17/05/2018	76	01/08/2018
Reyl & Cie S.A.	Ohman Bank SA	20/09/2018	192	31/03/2019
Pareto Securities AS	Aktieinvest FK AB	18/10/2018	83	09/01/2019

Table III - Mergers that identify treatment and control firms

Acquiror Name	Target Name	Date Announced	Number Of Days	Date Effective	Threshold ⁵⁰
Chase Manhattan Ahorro S.G.I.I.C., S.A._NLE	JP Morgan	13/09/2000	109	31/12/2000	0.5 %
Allianz	Nicholas-Applegate Capital Management, LLC_NLE	18/10/2000	119	14/02/2001	1 %
AXA Group	Finaxa SA	19/04/2005	241	16/12/2005	1 %
Blackrock	Barclays Global Investors Japan Ltd._NLE	11/06/2009	173	01/12/2009	0 %
AcomeA SGR S.p.A.	Leonardo SGR S.p.A._NLE	31/01/2011	150	30/06/2011	0 %
KBC Asset Management N.V.	KBC Towarzystwo Funduszy Inwestycyjnych S.A.	17/01/2012	155	20/06/2012	0.5 %
Vienna Insurance Group AG Wiener Versicherung Gruppe	AXA Group	23/12/2013	165	06/06/2014	1 %
Aviva PLC	Friends Life Group Ltd	21/11/2014	140	10/04/2015	1 %
Liontrust Asset Management PLC	Alliance Trust Investments Limited_NLE	14/12/2016	110	03/04/2017	0 %
Seven Investment Management LLP	Tcam Asset Management Limited_NLE	17/05/2018	76	01/08/2018	0 %

Table IV – List of country of exchange of firms include in my sample

France
 Switzerland
 Netherlands
 Denmark
 Germany
 United Kingdom
 Russia
 Sweden
 Italy
 Finland
 Spain
 Republic of Ireland;
 Belgium
 Austria
 Norway
 Portugal
 Greece
 Luxembourg
 Poland

⁵⁰ it is the threshold of the blockholding at which I identified treatment and control firms;