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ZOMBIE FIRMS AND MONETARY POLICIES: THEORETICAL AND EMPIRICAL EVIDENCE

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. . . ad Enzo e Giovanna.
Grazie per avermi mostrato il valore dell'amore incondizionato.

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Introduction

In his study of economic development, Joseph A. Schumpeter conceived the theory of “Creative Destruction”. The economist argues that, the creation of new processes and the replacement of old businesses with innovative ones is a driving force of capitalism and a necessary passage for the economic progress. Therefore, the legal institution of bankruptcy is fundamental to allow the correct reallocation of capital and resources and the smooth functioning of the economic system. Under certain conditions, however, the normal process of market exit of unproductive firms may not work. This contributes to the creation of market distortions that are able to affect industries and the overall economic environment.

The rise of zombie firms, defined as companies that are unable to cover debt servicing costs from current profits over an extended period, is a complex phenomenon that has attracted increasing attention both by academics and policymakers. In particular, its popularity has spiked during economic downturns, when the fear of a wave of corporate bankruptcies increased. The Covid-19 pandemic has given further impetus to this debate as the crisis puts severe strain on the corporate sector and governments and central banks rush to provide massive stimulus to the economy. The relatively young literature on zombie firms has focused mainly on the causes and consequences of their growth. A large number of researches have discussed the impact zombies have on healthier companies. The mainstream position of the literature is that zombie enterprises may create the so-called “congestion effect”, provoking negative repercussions on profitability, employment and investment levels of healthier firms. However, an innovative and opposite argument discussed by Schivardi et al. (2020) can drastically change the paradigm. In their two companion papers, the authors argue that previous studies suffered from a serious “identification problem” that led to report incorrect conclusions.

Regarding the cause that stimulate the emergence of zombie companies, two main factors are addressed in the literature: forbearance lending and monetary policy. The first describes a situation in which banks present structural weaknesses that encourage the adoption of risky actions such as the practice of “zombie lending”. The second is related to the benefit a fall in interest rates brings to heavily indebted firms. The latter argument, has been studied significantly less and researches have only been limited to specific monetary tools. Motivated by these facts, the empirical part of this thesis aims to provide a general model to explain how monetary policies can influence zombie companies. Central banks affect loan supply through interest rates decisions and open market operations. On the one hand, lower rates may reduce pressure on debtors to improve their balance sheets and on creditors to recover expected losses; on the other hand, liquidity injections increase the amount of cash reserves of the banking system, altering banks' credit supply and risk aversion. In specific settings, studies have seen that distorting mechanisms show up and part of this liquidity is misallocated to unproductive firms causing zombie lending. The model aims to describe this link by analyzing two channels: the first is the bank lending channel, i.e. the financial structure that connects central banks' monetary policies to the banking sector; the second is defined by the credit relationship banks have with companies. Therefore, a two-stages least-squares probit regression model will be developed, where the money supply directed to banks is used as instrument and the corporate loan volume of banks is the endogenous variable. The analysis investigates the causality link between the credit supply and the likelihood of a zombie firm to obtain credit. In particular, using margins analysis and isolating the effect of the endogenous variable, it will be possible to understand the impact expansionary monetary policies and credit supply have on the probability of zombie firms to receive credit.

The COVID-19 pandemic crisis represents a renewed threat of zombie firms' proliferation. The nature of the shock itself, impacting the corporate sector directly and the unprecedented support measures implemented by central banks and governments are factors able to trigger a rise in zombie enterprises. The health crisis quickly spread around the world, forcing the imposition of severe social restrictions that froze financial markets and disrupted demand, supply and value chains. In particular, the COVID-19 pandemic has caused a large re-pricing and re-positioning in global financial markets. The high uncertainty about the future development of the pandemic implied a sudden increase in risk aversion in corporate debt markets and extreme volatility in markets for risky assets. Policymakers response was prompt and on a large scale. Governments and central banks reacted strongly to avoid a new financial crisis, coordinating fiscal and monetary policies. At the same time, social restrictions imposed to limit the virus have affected the corporate sector both in the short and in the long-term. Revenues and profits have significantly declined in many industries and consumption patterns have changed dramatically. In this contest, the rise in the share of zombie firms is a possibility that concerns policymakers. Nevertheless, researches have proposed a number of policies directed to avert a wave of corporate "zombification" and foster a more viable recovery.

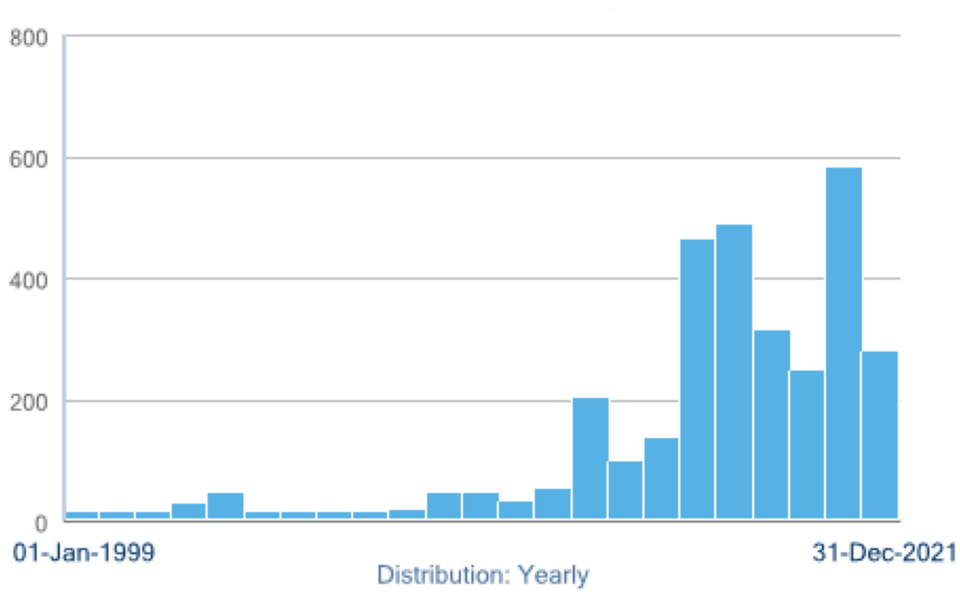
The work is organized as follows. Chapter 1 presents an overview of the concept of zombie firms, introducing the literature, the characteristics and the trends typical of these companies. Then, a broad discussion is made on the causes and consequences of the rise in zombies. Finally, the identification problem raised by Schivardi et al. (2020) will be analysed in detail. Chapter 2 explores the empirical evidence of monetary policy's influence on zombie lending. The first section presents the data selection and the analysis of the data set construction and composition. Then, the econometric background is reviewed with a focus on the probit model, the two-stages least-squares regression technique and the maximum likelihood estimation method. The last section describes the model outline, its implementation and the interpretation of the results. In the last chapter the COVID-19 pandemic crisis and its impact on zombie firms are examined closely. After a general introduction, the second section looks at the immediate effects on financial markets and the response of monetary policy in both advanced and emerging market economies. Then, the short and long-term effects of COVID-19 on the corporate sector are analysed with a particular focus on the influence on zombie firms. Finally, the best policies to prevent zombification will be discussed in detail.

Chapter 1

The Phenomenon of Zombie Firms

The term “zombie firm” comes from the study of Caballero et al. (2008) on the causes that led to the Japan’s “*Lost Decade*” of the 1990s. Since then, and especially in the last decade, the topic has gained large attention in academic and political circles due to the rapid ascent of the phenomenon as showed in *figure 1.1*. The Great Financial Crisis (GFC) and more recently the COVID-19 pandemic, have further fuelled the discussion on the subject.

Figure 1.1: Public Debate on Zombie Firms



Number of times per year the word “zombie firms” appeared in English-language newspapers and news magazines as well as in blog or board entries.
Source: own elaboration from Factiva

In very general terms, a zombie firm can be conceived as a company that is not operatively profitable but it is still sustained with credit. The definition of zombie firms is a debated concept and in fact, there are a number of identification strategies in the literature. The first, developed by Caballero et al. (2008) and then followed by others, defines a firm as zombie if it receives a “subsidised credit”. In particular, a credit can be considered subsidised when is granted at rates that are below those for the most creditworthy companies. This identification method, however, has three potential drawbacks. First, identifying such credit with precision is difficult. Second, banks may grant subsidised loans for other reasons, such as long-standing relationships. Finally, when interest rates are very low for a long time, subsidised lending rates would have to be near zero or even negative. Therefore, researchers have come up with another identification method based on companies' profitability and described first by Adalet McGowan et al. (2017). This has been named later on "broad" and classifies a company as zombie if its interest rate coverage ratio (ICR), defined as earnings before interest and taxes (EBIT) over interest payments, is below one for at least 3 consecutive years[1]. In this way, it is possible to account for persistent lack of profitability and low performance. Following this reasoning, another identification method discussed by Banerjee and Hofmann (2018), has been developed. This, instead, is called "narrow" and considers the addition of a low stock market valuation as indicator for low future growth expectation. Specifically, it requires a zombie firm to have the ratio of its assets' market value to replacement cost (Tobin's q) below the median within its sector in any given year. This last extension tries to avoid identifying as zombie firms those that may make losses currently but have positive growth perspectives such as young companies or start-ups.

This chapter presents an overview of the key aspects concerning the topic of zombie firms. Therefore, the main objective will be to provide a general and comprehensive discussion on the subject and prepare the reader for what will be found subsequently. In addition, the chapter has the function to disclose the key contributions in the literature so far, describe the themes of future development and present the remained open questions. The structure of this chapter is as follows: the first section illustrates the documentation on zombie firms in the literature. Then, the main characteristics and trends of zombie firms are discussed with a particular attention to their financial conditions, long-term behaviour and sector distribution. Third, the section reviews the causes of the rise in zombie firms in the last decades presenting the analytical results of researchers. Later, the consequences of the rise in zombies in the economy are examined. Finally, the innovative finding of the identification problem by Schivardi et al. (2020) is discussed in detail.

1.1 Literature review

The first authors to provide evidence on banks extending credit to weak borrowers are Peek and Rosengren (2005). Their paper focuses on firms and banks in Japan during the 1990s, when the economy suffered from high levels of non-performing loans, weak growth and a low interest rate environment. Their study finds that weakly capitalised banks are more likely to lend to poorly performing borrowers in the attempt to avoid realizing losses on outstanding loans. Then, Caballero et al. (2008) highlight this phenomenon as a potential factor for Japan's lost decade, a prolonged period of economic downturn that lasted during the 1990s. Their idea is to identify zombie firms as those receiving subsidize loans. This definition depends on the actual interest rate paid and its

[1]These are two accounting terms used to identify gross profit after amortisation and depreciation and the ratio between gross profit and interests paid on debt

difference with a theoretical benchmark. According to the paper, up to 30% of publicly traded firms received subsidised credit after the Japanese crisis. The authors show that the increasing number of zombie firms in Japan in the 1990s was mainly driven by weakly capitalised banks. These agents often chose to roll-over bad loans instead of writing them off to avoid bearing losses that would have led them to exceed capital requirements. The authors also build a framework to measure the indirect costs of zombie firms suppressing the normal competitive process. In fact, the market "congestion" created by these firms reduced healthy firms' profitability, and in this way, depressed investment and employment levels. As a consequence, zombie-dominated industries displayed lower job creation rates and productivity. Giannetti and Simonov (2013) use the same method of Caballero et al. (2008) to identify zombie firms and study the effect of the Japanese government series of bank bailouts in the aftermath of the 1990s crisis. The authors find that re-capitalisation large enough to enable banks to meet their capital requirements, actually increased borrowers' access to credit supply. Moreover, this increase in borrowing has implication on the real economy. They observe that these firms were able to increase investments and improve their valuations. On the other hand, insufficient recapitalisation produced the opposite effect: the increase in credit supply was mainly directed towards zombie firms which were also the only ones to increase investments. A number of studies has instead analysed the main trends affecting zombie firms. Adalet McGowan et al. (2017) record a significant increase in the number of zombie firms across advanced economies subsequent to the Great Financial Crisis. The authors, following Caballero et al. (2008), explain the prevalence of zombie firms in some industries with lower aggregate labour productivity. Banerjee and Hofmann (2018) document a long-term trend in the increase in zombie firms that starts in the 1980s. According to their study, zombie firms are less productive and cause congestion effects for healthier firms, crowding out resources. They also affect the economy, reducing its ability to innovate and lowering profits in the markets. Differently from previous papers, these studies set out new identifying strategies based on companies' performance[2]. Another recent important contribution to the literature is made by Schivardi et al. (2020). In these two companion papers, the authors argue that the literature so far faces an identification problem. This is caused by a bias in measuring the correlation of the performance of non-zombies with the sectoral share of zombies. In these papers, the authors state that the shocks caused both by adverse events and policies are uncorrelated to firms' financial health. Therefore, they propose as a solution to find an exogenous variation in the share of zombies with respect to the aggregate shock. If corroborated by other studies these findings could change the way the economic literature assesses zombie firms' effects on their healthier peers.

Many reports have also considered the role of persistent low interest rates as a key driver of the recent increase in zombie firms. Yet, there are few studies that cover this topic analytically. Banerjee and Hofmann (2018) show evidence of a statistically significant link between low rates and the number of zombie companies at the country and industry level. Acharya et al. (2019), instead, focus on the real effects the ECB's Outright Monetary Transactions (OMT) program produced on economic growth. In particular, they document zombie lending by banks that remained

[2] The methods are described in the introduction of this chapter

weakly capitalised even post-OMT. The authors focus on the concept of "stealth recapitalisation"[3] on bank lending following the OMT announcement. The paper highlights that a stealth recapitalisation measure can lead to credit misallocation due to zombie lending. The empirical section analyses first the extent to which individual banks were affected by the OMT announcement. To do so, the authors use data on banks' sovereign debt holdings and the changes in sovereign bond prices to construct a variable called *OMT windfall gain* that measures how much a bank's equity increased due to the OMT announcement. The results demonstrate that banks with significant holdings of bonds issued by stressed European countries (the GIIPS countries, i.e., Greece, Ireland, Italy, Portugal and Spain) realized the highest windfall gain, increasing their capitalisation. The improvement in the banks' financial health led to an increased loan supply post-OMT, which was proportional to the level of windfall gains. Then, they focus on banks' lending behaviour. In particular, the analysis covers which type of borrowers benefited the most from the higher lending volume post-OMT. Based on their profitability and ability to repay existing debts, namely EBIT and ICR, they find that low-quality pre-existing borrowers (often zombie firms) are the principal beneficiaries of the additional credit supply.

This thesis is related to the strand of literature that addresses the effects financial policies have on *zombie lending*. The innovative contribution of this work is to provide a model to explain the general process that allows money supply to influence zombie firms, passing from the banking sector. This will be further discussed in Chapter 2, the empirical section.

1.2 Zombie firms' characteristics and trends

Taking a deeper look at the anatomy of zombie firms it is possible to highlight a number of key characteristics that distinguish them from healthier companies. Many studies find that zombie firms increase with age and size[4]. These two distributions can have several explanations. First of all, larger and older firms have usually more solid relationships with banks, thanks to their long presence in the market and more transparent reporting systems. Therefore, they may have built a reputation that allows them to receive funds even in period of low profitability. Moreover, when firms have longer relationship with banks the hypothesis of loan restructuring implies an higher sunk cost. Finally, larger firms are more likely to receive subsidies funds from the government, especially in periods of crises, due to the greater occupation loss they would cause. On the other side, a couple of other papers[5] find that zombie firms are usually represented by small and medium-sized enterprises (SMEs). The definition method is a large discriminant here, since when considering the narrow measure only listed firms (which are mainly large companies) are considered. However, the authors show that among listed SMEs, the share of zombie firms is considerably higher than in larger firms.

Zombie firms present also different investment behaviour from profitable companies. Further

[3] An indirect recapitalisation through a price appreciation of bank security holdings; see Brunnermeier and Sannikov 2016

[4] See: Adalet McGowan et al. (2017) and Hallak et al. (2018)

[5] See: Banerjee and Hofmann (2020)

studies find that, on average, their capex is 0.5 percentage lower in terms of assets and their research and development investments (R&D) are also substantially lower, in the range of 1.2 percentage points. Zombie companies see their operative activities decrease and this is reflected by higher asset disposal (0.5 percentage point higher) and diminishing employment (6% decrease compared to 3% growth in non-zombies). They are less productive than other firms, with both labour productivity and total factor productivity only half the level of non-zombies. By definition, zombies are characterised by negative cash flow and ICRs and low values of Tobin's q, therefore this profitability weakness also implies that these firms pay out lower dividends. Looking instead at the capital structure, zombie firms are more levered when measured as total debt to total asset ratio. However, the absolute value of debt has a decreasing trend, probably reflecting some constraints in obtaining new debt or efforts to reduce their leverage. Finally, the probability of exiting the market for zombie firms is twice as high as that of non-zombies (8.5% vs. 4%)[6].

Taking a longer-term perspective, it is possible to notice that the share of zombie companies has increased over time, with sudden shift, in the wake of economic recessions that were not completely offset by subsequent recoveries. According to Bank of International Settlement (BIS) researches, both the measures discussed for the identification suggest that the number of zombie companies has increased substantially since the 1980s. Looking at a set of 14 advanced economies[7], the share of zombies among all other firms rose, according to the broader measure, from 2 percentage point at the end of 1980s to 15% in 2017, and from 1% to 6% under the narrow definition. As shown in *figure 1.2*, the increase was largely affected by economic downturns in early 1990s and 2000s and after the GFC of 2008. Therefore, it is reasonable to expect another sudden spike in the wake of the COVID-19 pandemic. These upward shifts were only partly recovered in the following years, especially after the GFC, which had more prominent effect raising the share of zombie firms to a peak of 16% in 2010. The rising number of zombie firms in the economy is determined by the intrinsic characteristic of this type of companies. The status of zombie firm is strongly persistent and its durability has increased over time. Rather than return to an healthy state or exit the market because of bankruptcy, zombie firms tend to remain so for longer periods. The probability of a zombie company remaining zombie increased from 60% in the 1980s to 85% in 2017 considering the broad definition, and from 40% to 70% in the narrow measure.

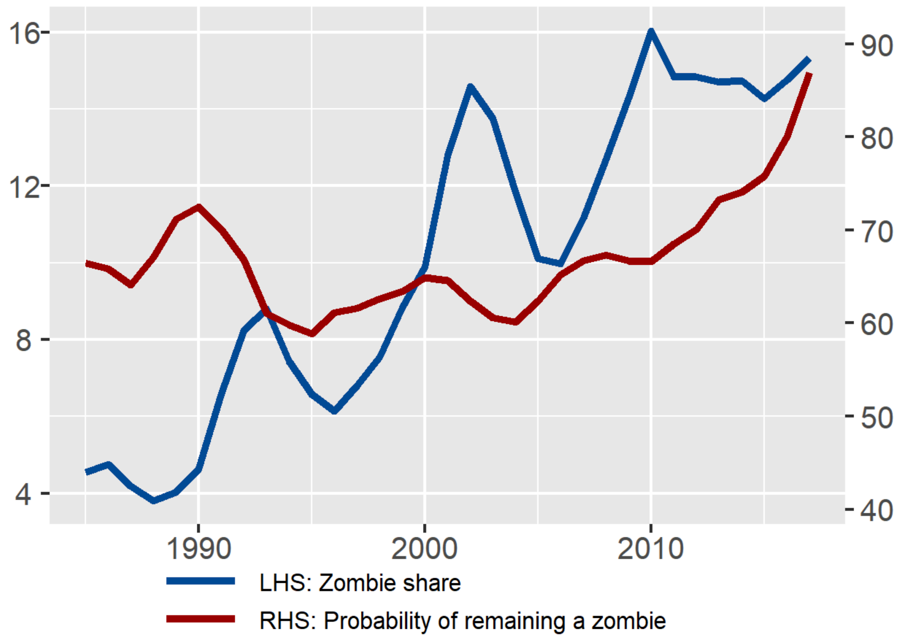
Another important topic to explore is how much zombie companies weight in the economy. In order to assess this measure, it is possible to use the share of zombie firms in the total assets of all listed non-financial companies[8]. The results of the BIS show that zombies are probably economically less important. On average, the economic weight of zombie firms is lower than their actual number, since about 6-7% of assets, capital and debt are sunk when considering these companies. However, the definition method leaves a big question mark on the actual economic significance of zombie firms. In fact, among SMEs the same measure of share of zombie assets

[6] Where a firm is considered exit/death when they exit the Worldscope database because are either: "DEAD","MERGER", "TAKEOVER" or "LIQUIDATED"

[7] Data are downloaded from the Worldscope database and indicates zombie firms for Australia, Belgium, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom and the United States

[8] Measured as total zombie assets (capital and debt) over that of all listed firms

Figure 1.2: Zombie firms share and persistence



Zombie shares and probability of remaining a zombie over time.
Source: Banerjee and Hofmann, "The rise of zombie firms: causes and consequences"

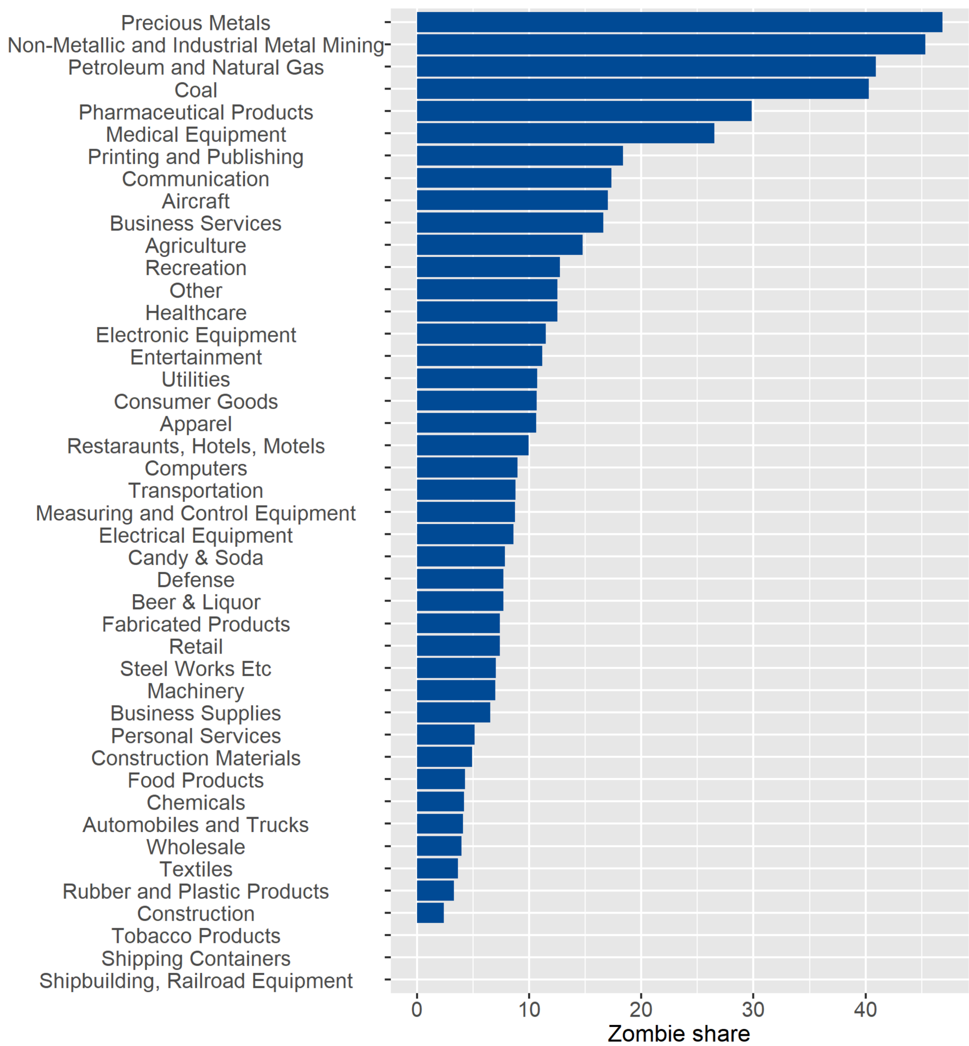
over all firms is significantly higher (around 30-40% more) with respect to large firms. If SMEs are actually more numerous when considering zombification, this would go unnoticed in the narrow definition. As a consequence, since the majority of them are non-listed, the real weight of zombies on the economy could be much larger.

The problem of including SMEs is clear also when considering cross-country differences. Banerjee and Hofmann (2018) show that the difference in the propensity to list companies in each country impact on the aforementioned ratio. In fact, the share of zombie companies is higher in Anglo-Saxon countries such as Australia and Canada (30%) and United Kingdom and United States (20%). In these economies there is a wider tendency to list companies, including SMEs. The share of SMEs, defined as companies with an annual turnover of less than 50 million US dollar[9], on the total population of listed firms was about 50% in Anglo-Saxon countries in 2017. Differently, in continental Europe and in Japan the share of SMEs in all listed companies was 28% on average and 15%, respectively. The European countries considered have a presence of zombie firms that range from 10% to 15%. Except for France for which the share more than doubled since 2008, the number of zombie firms on the population of companies remained steady after the GFC and the subsequent Sovereign Debt Crisis. Again, if SMEs are actually more likely to be zombie firms, the higher share of zombies in Anglo-Saxon countries reflects the larger number of listed SMEs among all listed firms. Consequently, it is possible to infer that in continental Europe and Japan the real zombie share over all companies is probably higher than what thought.

[9]This definition is adopted by the European Commission. Another criterion defining an SME is that the number of employees should be below 250, however data on turnover are far more accessible

From *figure 1.3* It is also possible to notice a significant variation in zombie shares depending on the industry. The share of zombie firms is higher in commodity sectors (40%). A possible interpretation is given by the importance these industries have on countries that present the higher percentage of zombie shares, such as U.S. and Australia. Furthermore, the commodity market has been in the centre of a twenty-year decreasing trend that has largely affected its profitability. The second largest industry by zombie firms share is the healthcare sector. This might change in the wake of the COVID-19 shock, which could boost the profitability and stock valuations of these firms, just as it could dampen them in other sectors that used to be characterised by low degrees of zombification (e.g. retail and transportation). Finally, the printing and publishing sector also has relatively high shares. The structural challenges from digitalisation could be a key driver here.

Figure 1.3: Zombie firms shares by sector



Zombie firms shares by sector in percentage in 2017.

Source: Banerjee and Hofmann, "Corporate zombies: Anatomy and life cycle"

Then, it is interesting to study what happens after a firm becomes zombie. According to data compiled by the BIS[10] on zombie companies starting in the mid-1980s, the majority (about 60%)

[10]See: Banerjee and Hofmann (2020)

of these firms have recovered from a previous zombie status. Instead, around 25% of them have died through market exit and the remaining 15% represents the active cases. Looking at these data, the problem of zombie firms could appear a temporary issue. To address this question, it is necessary to understand their health status in the long period by zooming closer on the fraction of zombies that has recovered. It turns out that firms which have previously recovered from the zombie classification face a high probability of relapse and in particular, this probability has significantly increased in the recent years. In 2017, the probability of a recovered zombie firms of becoming zombie again in the next period was about 17%. This probability has fluctuated a lot from 1980s, economic downturns have coincided with sudden increases, while subsequent recoveries are associated with considerable declines in the likelihood. The last twenty years nadir has been reached after the Dotcom bubble in 2005, when the probability of becoming zombie after recovering touched 5%. After that, there has been a steady and fast increase to the actual levels. On the other hand, the probability of turning zombie for firms that have never been zombie before is about 3%, essentially unchanged compared to the probabilities over the past two decades. Finally, it is possible to explore the differences between recovered zombies and healthy firms' performance indicators. Not only recovered zombies are more likely to relapse into zombie status, but they are also systematically weaker than firms that have never been zombies. They significantly lag in terms of assets, capital stock and employment, being smaller. As a consequence, they are less dynamic and productive. In fact, recovered zombies show considerably less investments in physical and intangible capital. Furthermore, the employment level increases at less than half the rate of firms that were not previously classified as zombie. At the same time, both their labour productivity and total factor productivity, is significantly lower than that of their peers. Overall, these results suggest that there seems to be a growing corporate vulnerability characterised by mediocre performance and a material risk of relapsing into zombie status. The percentage division reported above may therefore understate the true extent of weaknesses and risks present in advanced economy corporate sectors.

1.3 Causes of the rise in zombie firms

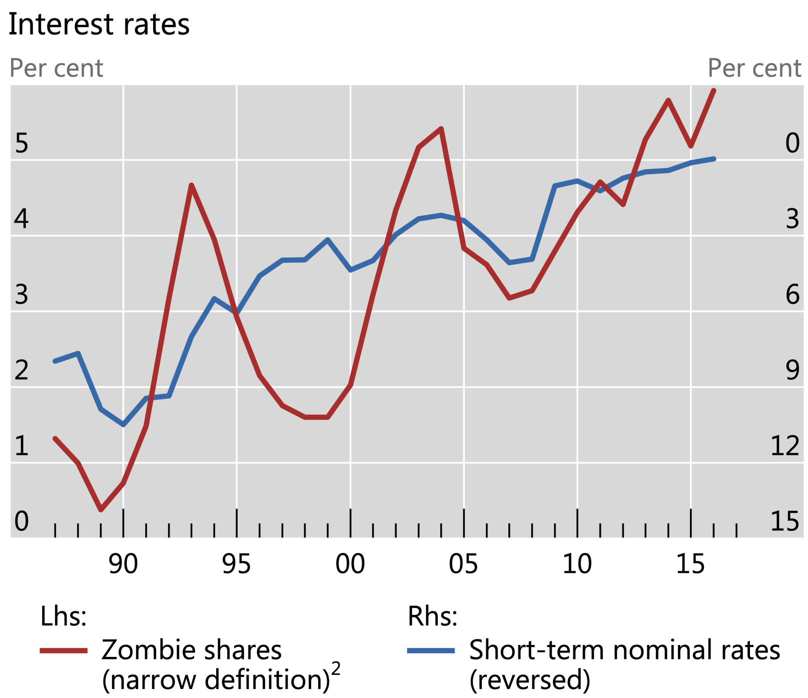
Zombie firms are increasing in numbers, tend to survive more and impact on firms' profitability even after recovering. Their importance in the economy is becoming more evident and policymakers are trying to understand how to limit this phenomenon. However, to recognize and adopt adequate countermeasures, it is necessary to comprehend what reasons lead to the rise in the number of zombie firms. The literature has identified two key causes that may produce the conditions needed for zombie firms to thrive. The most studied practice that gives rise to this phenomenon is bank weakness and forbearance lending. At a first glance, it is difficult to imagine why banks should lend to non-viable firms. In corporate finance theory, a bank underwrites only loans that produce positive net present value, namely a profit on the investment. However, some banking dynamics create an incentive to deviate from this optimum and allocate resources in unprofitable projects. In a nutshell, when banks have impaired balance sheets and are close to exceed capital requirements, an incentive to misbehave is produced creating the practice of "zombie lending". In this situation, banks might prefer to roll over credit to non-viable companies instead of writing them off to cover for potential losses and their consequences.

The first studies on zombie lending focused on the Japanese economy from the 1980s to 2000s. Peek and Rosengren (2005) provide bank-firm evidence that the least capitalised banks were the more likely to "evergreen" credit to unproductive companies, while Caballero et al. (2008) quantify the presence of zombie firms identified as those receiving subsidised loans. Okamura (2011) find evidence that the root cause of zombie firms in the Japanese banking crisis of 1997-2003 were under-capitalised banks. The author states that Japanese banks took advantage from the side effects created by regulatory forbearance and this led to large flows of credit towards zombie firms. Regulatory forbearance happens when regulators are not able to enforce weak banks to recapitalise or go bankrupt. Insolvent or under-capitalised banks, may prefer to bet for resurrection with riskier choices by allowing unprofitable firms to operate instead of writing-off loans and consequently reduce capital. Giannetti and Simonov (2013) use the same method of Caballero et al. (2008) to identify zombie firms and show that only recapitalisation that are large enough to allow banks to meet capital requirements lead to increased credit supply for borrowers with a long-lasting lending relationship. Instead, small recapitalisations relative to a bank's financial condition are ineffective. Further analyses have been carried out on the European case after the GFC and the sovereign debt crisis. Acharya et al (2019), find that weakly capitalised banks were the ones that benefited the most from unconventional monetary policies, in particular the Outright Monetary Transactions (OTM). These gains however, were widely used to refinance zombie firms. Besides, Storz et al. (2017) study whether banks in euro area periphery countries (Greece, Ireland, Portugal, Spain and Slovenia) delayed the deleveraging of zombie firms and compare them with core European countries (Germany and France). In this setting, a one standard deviation increase in the bank stress measure force a 1 percentage point raise in leverage of zombie firms annually. Interestingly, the effect is significant only in euro area periphery economies while in core countries the impact is not present, indicating that weak banks are more inclined to undertake risky operations in distressed economies. Another paper by Schivardi et al. (2020) uses data on bank-firm relationships to analyse the behavior of under-capitalised banks in Italy during the euro zone financial crisis. The authors find that these banks were more likely to continue lending to zombie firms and cut credit to healthy firms than their healthier peers. As a consequence, this increased the survival rate of zombie firms and affected the composition of bankruptcies. As shown by other economists before, weaker banks try to delay or hide losses from supervisors by rolling over these loans instead of writing them off. In a period of economic downturn like this, capital requirements are raised to prevent financial crisis. Banks that do not meet these conditions may try to raise capital which tend to be particularly expensive given the higher uncertainty. As a consequence, agents tend to delay recapitalisation until aggregate economic conditions improve. This creates an incentive for all banks to hide losses, especially for those with less capital since they face more pressing recapitalisation requirements. Therefore, not only zombie firms are less likely to be impacted by the credit contraction, but they are also less likely to see the termination of their credit relationship.

Furthermore, the relative effect on zombie firms versus healthier companies is stronger if credit is not collateralized, since the default of an uncollateralized loan has a stronger impact on regulatory capital.

A second important factor in explaining the rise in zombie firms is the downward trend in interest rates. Differently from forbearance lending, this cause has not been studied analytically as a whole. Theoretically, interest rates may have a contrasting effect. On the one hand, lower rates should improve the overall ICR ratio by reducing interest expenses and therefore, diminish the share of zombie firms. On the other hand, a reduction in interest rates lowers the pressure on creditors to deleverage and improve their balance sheets. As a consequence, this creates an incentive to evergreen loans to zombie firms. This counter-effect is possible because banks choose to minimize the opportunity cost of cleaning up, decreasing the funding cost of bad loans and increasing the expected recovery rate on these loans. Substantially, lower rates may create incentives for risk-taking through the monetary policy channel. Since zombie companies are riskier debtors and investments compared to solid borrowers, more risk appetite should reduce financial pressure on them. These mechanisms could operate through nominal or inflation-adjusted (real) interest rates, but nominal ones might in practice be more relevant if there is money illusion. From *figure 1.4* it appears that

Figure 1.4: Zombie firms share and interest rates trends over time



Evolution of zombie firms shares and short-term nominal interest rates (reversed) over time.
Source: Banerjee and Hofmann, "The rise of zombie firms: causes and consequences"

the share of zombie firms is actually negatively correlated with interest rates over time. The increasing share of zombie firms in the economy and the falling interest rates high correlation can be explained by the lower pressure to deleverage and the chance for banks to increase the recovery rate of impaired loans. However, the relationship could also arise due to reverse causality: the raising share of zombie companies, depressing productivity growth pushes down interest rates in the long run. Another alternative is that the correlation could be caused by a common originating factor: if aggregate productivity falls, this implies a lower level of investment opportunities and therefore reduced interest rate. To check these hypotheses, Banerjee and Hofmann (2018) test whether changes in interest rates are able to predict future zombie shares. To do so, they applied the Granger causality tests[11] on a country panel data over the period 1987-2016. The resulting regression suggests that nominal interest rates predict the actual increase in the zombie share. The causal correlation is statistically significant and external to reverse causality or omitted variables problems. Therefore, the results are consistent with a role for interest rates. Lower nominal interest rates lift the share of zombie firms in those sectors where companies are more dependent on external funding. The authors further estimate that the 10-percentage point decline in nominal interest rates occurred since the mid-1980s may account for around 17% of the rise in the zombie share in advanced economies when evaluated at the average industry external finance dependency ratio. The results remain robust when instead of nominal, real interest rates are used.

1.4 Consequences of the rise in zombie firms

The topic of zombie firms has gained relevance in the public debate because of the potential detrimental effects on the economy. The issue is based on the underlying logic that zombie companies, when are in considerable numbers, not only are able to lower aggregate productivity, but also to cause negative spillovers that may affect healthier firms.

Caballero et al. (2008) were the first to theoretically define the concept and measure the impact unproductive firms have on their peers. In particular, the authors state that by keeping zombie firms alive, banks allow them to suppress the normal competitive process. They argue that zombie companies create a congestion problem that reduces the profits other firms would normally do and impairs employment and investment levels. More specifically, zombie firms distort the markets in which they operate by reducing prices and increasing wages by keeping low levels of labour productivity. To analyse the market congestion effect, the paper looks at productivity and job creation for industries with different levels of zombie shares. The results confirm lower productivity and job creation rates for sector with significant shares of zombie firms. The empirical analysis, instead, focuses on the impact zombie firms have on healthier firms' behaviour through the congestion effect. The authors find a statistically significant relationship between the increase in the percentage of zombie companies and the fall in investment and employments growth in non-zombie enterprises. Furthermore, for what concerns the productivity gap between the two groups, this effect becomes larger as the percentage of zombie increases. Adalet McGowan et al. (2017), looking at possible explanations for the productivity slowdown in advanced economies over the past decades, support the same results. The survival of non-competitive firms may weigh on average productivity and crowd out growth opportunities, affecting the overall business environment. In particular,

[11]The Granger causality test, is a statistical hypothesis test for determining whether one time series is useful in forecasting another.

the authors link the rise in zombie firms since the mid-2000s and their ability to survive for longer to a growing congestion effect. The results of the paper show that higher shares of capital sunk in zombie firms lead to lower investment and employment growth in healthier firms. An innovative finding of this paper is that besides limiting the expansion of more productive firms, market congestion caused by zombie companies is able to create barriers to entry. The results are a supporting empirical evidence for the findings previously discussed for Caballero et al. (2008) that zombie congestion tends to widen the productivity gap between unproductive and productive firms. In fact, as zombie firms depress market profitability, entrants need to reach higher productivity to remain in the market. This effect is particularly important for young firms, for which the employment growth is even more sensitive to zombie congestion. Other recent studies have confirmed the results of Caballero et al. (2008). Banerjee and Hofmann (2018) outcomes are consistent with the hypothesis that zombie firms crowd-out growth of more productive peers by locking resources. In fact, labour productivity and total factor productivity of zombie firms are on average lower than non-zombies according to the broad and narrow definition. In particular, according to this report, a 1 percentage point increase in the share of zombie firms in a sector reduces healthier firms capital expenditure rate by 17% and their employment growth by 8% relative to the mean rate. The authors further isolate the rise in a country's share of zombie firms to measure their impact on non-zombie companies' productivity. They find that as the share of zombie firms increases by 1%, there is a significant decline in productivity growth of 0.3 percentage points. The idea that zombie firms are even more harmful for young firms is supported also by Issam Harasztosi et al. (2018). Studying the European corporate sector, the authors find that zombie firms may be a potential cause of the lack of dynamism and investments in the continent. Additionally, to assess the interaction between zombie and non-zombies, they construct a measure for zombie congestion by calculating the share of capital sunk by country and sector. The paper states that the employment growth of zombie enterprises is able to crowd out that of healthier peers, especially the young ones and that as the share of zombie firms gets larger, non-zombie companies are likely to grow less. Another study on the European corporate market is made by Tracey (2019), which analyses the extent to which forbearance lending contributed to low output growth in the euro area following the European sovereign debt crisis. The main finding of this paper is that aggregate output, investment and total factor productivity would have been considerably higher in the absence of forbearance lending. Zombie lending effects can be analysed also through the lens of monetary policy as in Acharya et al. (2019). In this paper, the authors document bank lending behaviour subsequent to ECB's Outright Monetary Transactions (OMT) program adding zombie lending among the reason for the ineffectiveness of this kind of measures. The results show that 8% of the credit granted was zombie lending, which distorted the normal competitive process of markets causing harmful effects on employment, investment and growth. Furthermore, they provide a measure to quantify the negative effect the rise of zombie firms post-OMT had on non-zombie companies. The authors find that zombie lending crowds-out credit to more productive firms and contribute to alter market competition by reducing prices and raising wages. Finally, an original paper by Acharya et al. (2020) detects a significant effect of zombie lending on inflation. In particular, cheap credit to unproductive firms creates an excess production capacity which in turn depresses prices producing a disinflationary effect. By studying twelve European countries firm-level data, the authors find that a rise in zombie credit is linked with lower aggregate default and entry levels, decreased productivity, mark-ups and product prices and higher material and labour cost. The partial equilibrium results estimate that, without a rise in zombie credit after 2012, the annual inflation rate in Europe would have been 0.45 percentage points higher in the period 2012-2016.

An innovative and opposite claim on the effect zombie firms have on more profitable companies is advanced by Schivardi et al. (2020) in two companion papers. In the first work the authors study the cost of credit and resources misallocation looking at the Italian case subsequent to the financial crisis. In fact, Italy represents an ideal sample since after the GFC it entered in a long recession, it was characterized by a large increase in non-performing loans (NPL) and experienced a prolonged credit crunch. In this period, differently from other European countries, Italy did not embark in banks recapitalisation programs nor it created a bad bank to absorb the NPL. Hence, banks were left free to choose how to react to the economic downturn and the stricter capital requirements that were imposed. The results show that under-capitalised banks kept granting loans to zombie firms, increasing the likelihood of prolonging their credit relationship. As seen in other studies, this occurred because weaker banks rolled-over bad loans seeking to hide losses from supervisors, in order to delay recapitalisation until circumstances turned more favourable. At the same time, these banks are more likely to cut credit to healthy companies. The consequence was a rise in the survival rate of zombie firms relative to non-zombies which in turn impacted on bankruptcies composition. Besides, another central finding of this paper is that bank under-capitalisation provided a source for faster zombie firms growth but did not affect healthier firms. According to the paper, despite weak banks actually misallocate resources to unproductive firms, affecting economic efficiency in the long run, forbearance lending did not produce harmful effects on non-zombie companies. Instead, by granting more credit to zombie firms banks are able to reduce supply chains shocks and aggregate demand externalities. In addition, healthier firms in the sample were able to continue to operate thanks to cash reserves and equity recapitalisation. As a consequence, zombie lending cannot be considered an inefficient side effect of growth and employment supporting programs since it has no consequences on the overall economic environment. These claims are in stark contrast with the mainstream literature on zombie firms and their effects. The authors argue that this divergence is due to a serious, and so far overlooked, identification issue which is further discussed below. The second paper of the three authors is focused on assessing the potential detrimental effect zombie lending may have in the wake of the COVID-19 pandemic. Since at the beginning of the COVID-19 crisis the banking sector was definitely more solid compared to the GFC and the sovereign debt crisis, the occurrence of zombie lending was less likely. Nevertheless, zombie lending can arise from various reasons alternative from weakly capitalised banks. For example, this might arise due to government or central banks programs designed to increase bank corporate lending, which during the pandemic were very popular. In this paper the authors indicate that there is no solid support for the idea that public policies that sustain corporate lending have negative consequences due to zombie lending. Then, linking the argument to the first paper, they refuse the common framework applied in the literature to estimate the effects zombie firms have on healthier peers. In particular, they claim that the mainstream procedure has an identification problem that biases the results towards finding negative spillovers even when it is not the case. Their conclusion is that zombie lending does not represent a sufficiently significant risk for government to not put into place credit guaranteed programs in emergency situations such as the COVID-19 pandemic.

1.5 The identification problem

The effect zombie lending has on the economy is arguably the most important issue around the topic of zombie firms. To take thoughtful decisions, policymakers often rely on the empirical results academics and researchers find. However, due to certain complex dynamics, sometimes economists do not agree completely on what is the correct interpretation. As discussed above, the general wisdom of the existing literature on zombie firms argues that granting loans to unproductive firms tends to have detrimental effect on healthier firms and the economy as a whole. Keeping zombie firms alive implies a misallocation of financial resources which are diverted to low productivity firms and inefficient use. In particular, zombie lending has two main effects: first, it depresses the amount of credit available for healthy firms; second produces the condition for subsidising companies that create negative aggregate effects in their industries, such as lower profitability and productivity.

A different and innovative claim is proposed by Schivardi, Sette and Tabellini in two papers that challenge the mainstream literature on the effects of zombie lending. The authors claim that the previous empirical studies face a serious identification problem that produce a bias towards observing the presence of negative spillovers, even when this is not the case. Instead, they show that under general conditions on firms' performance distribution, there is no causal meaning between the increase in the share of zombie firms and the consequent correlation between healthy and zombie companies' performance. In fact, when firms are heterogeneous, an increase in the share of zombie firms is associated with a change in the composition of the groups of firms. Under standard assumptions on the firm performance distribution and in absence of any spillovers, this leads mechanically to a lower difference between the two groups means. Furthermore, the approach followed by Schivardi et al. (2020) aims to estimate the absolute effects of bank undercapitalisation on the performance of healthy firms and not the one relative to zombie firms. The results confirm that while the relative effect remain significant the absolute one is not. The general approach followed in the literature uses the following regression to assess the effects zombie firms have on healthier peers:

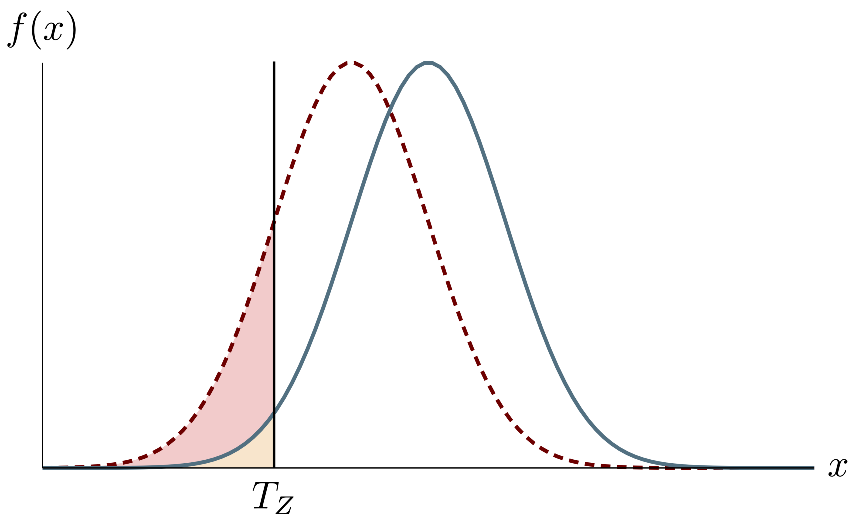
$$X_{ijt} = \beta_0 + \beta_1 D^{NZ}_{ijt} + \beta_2 Z_{jt} + \beta_3 D^{NZ}_{ijt} * Z_{jt} + D_t + D_j + \varepsilon_{ijt} \tag{1.1}$$

where X is a measure of activity (say employment growth) of firm i in sector j and year t, D^{NZ} is a dummy equal to 1 for non-zombie firms, Z_{jt} measures the presence of zombies in a sector, D_t and D_j are year and sector dummies and ε_{ijt} is the error term. While the coefficient β_1 measures the correlation between the share of zombies in the sector and the zombie performance, β_2 captures the differential effect for non-zombies. A negative estimate of the β_2 coefficient is interpreted in the literature as evidence of negative spillovers from zombies to non-zombies: the higher the share of zombies, the worse the relative performance of healthy firms. The identification problem in this regression comes from the share of zombie firms, since it may be correlated with the shock. For instance, a demand shock would be able to affect both zombie and non-zombie firms. In particular, a negative demand shock in sector j implies that the share of zombie increases and at the same time the performance of healthier firms operating in the same sector deteriorates. The problem is well known in the literature and it is usually limited by specifying the vector of dummy variables as a full set of country-sector-year dummy variables D_{jt}:

$$X_{ijt} = \beta_0 + \beta_1 D_{ijt}^{NZ} + \beta_3 D_{ijt}^{NZ} * Z_{jt} + D_{jt} + w_{ijt} \tag{1.2}$$

in equation 1.2 it is not possible anymore to estimate the absolute effect of the presence of zombie firms in a sector, but only the relative effect of non-zombies with respect to zombie, β_3. In a standard setting of firms' heterogeneity, this is not sufficient to interpret the coefficient as if zombies are able to negatively affect healthier peers, in relative sense. The problem is illustrated in *figure 1.5*, where the blue curve represents the hypothetical distribution of firms' performance in a given sector, with mean equal to five and unit standard deviation. The x-axis measures the performance of a firm, like growth rate and the threshold T_Z identifies the boundary between zombie and non-zombie companies. What matters is the difference between the average performance of healthy

Figure 1.5: Effect of a shock on zombies and non-zombies



Plots of two normal distributions representing the distribution of firms' performance i a given sector.
Source: Schivardi, Sette and Tabellini, "Identifying the Real Effects of Zombie Lending"

and zombie firms, $\mu_{NZ} - \mu_Z$. In particular, it is important to understand how exogenous changes in Z_{jt}, such as distortions of competition or lower credit supply to healthy firms, affect $\mu_{NZ} - \mu_Z$, the share of zombies in sector j at time t. The mainstream framework of the literature measures this effect by estimating β_3 in equation 3.2, which reflects the conditional correlation between the share of zombies Z_{jt} and the relative performance of healthy firms $\mu_{NZ} - \mu_Z$. The main assumption behind this reasoning is that in the absence of spillover effects, shocks that impact on the share of zombie firms affect equally the average performance of zombies and healthy companies, leaving the difference between means unchanged. However, if a negative shock hits the sector the curve moves to the left and the dashed red curve is obtained. In this case, the share of zombie firms Z_j increases because the area to the left of the threshold line is larger, moreover both the conditional means of μ_{NZ} and μ_Z are expected to drop[12]. Finally, the difference between the two conditional means $\mu_{NZ} - \mu_Z$ is also supposed to change because it depends on the shape of the distribution of firms' performance. This last consequence has been neglected by the traditional approach and has the power to lead to deceptive conclusions on the effects of zombie firms on healthier companies.

To prove that the results previously found in the literature are biased, the authors replicated the regression approach on a large sample of Italian firms for the period 2008-2013. Although there are some differences in terms of data and institutional setting, they obtained similar results of Caballero et al. (2008) and Acharya et al. (2019) for capital and employment growth. However, these findings cannot be interpreted as evidence of the effect of negative spillovers of zombie firms on non-zombie enterprises since they are biased by the mechanical correlation described above. In fact, when the authors replaced the share of zombie firms on the right-hand-side of equation 1.1 with an exogenous supply side variable describing bank lending to zombie firms, they did not find significant evidence of detrimental effects of zombie lending on healthy firms. In their paper, Schivardi et al. (2019) used low bank capital, as opposed to share of zombie firms, as a source of exogenous variation in the number of zombie firms. Thanks to this different approach, the authors were able to measure the absolute effect of banks' under-capitalisation on the growth of healthy firms.

[12] More details in Schivardi et al. (2020)

Chapter 2

Empirical Evidence of Monetary Policy Influence on Zombie Firms

The model developed in this thesis tries to identify a path that explains how credit can flow from central banks to zombie firms. Among their tasks, central banks set policy rates and provide liquidity to banks, which in turn use these funds to finance companies' operations. Therefore, the model focuses on two channels: the first is the one through which money supply is transferred to the banking sector[1], the second is represented by the credit relationship banks have with firms. Looking more in detail, the model investigates the role ECB's open market operations, directed to banks, have had on the likelihood of zombie firms to obtain credit. The time period under consideration is the last ten years, from 2011 to 2020, when the ECB has actively put into place unconventional expansionary monetary policies. The following chapter discusses the implementation of the empirical analysis and the interpretation derived from the results obtained. It starts with a description of the data sources, the steps put into place to manipulate and organize the data set and the construction strategy of the final panel data set. Then, the resulting outcome is further analysed, looking at the sector and national composition of the zombie firms present in the data set. Further investigations are done on the ability of banks in the data set to represent the syndicated loan market in the eurozone. Next, the econometric background of the model is discussed. In particular, the role and the application of the probit model is illustrated first, then the theory of the two-stages least-squares regression and the concept of maximum likelihood estimation are reviewed. Finally, the chapter examines the blueprint of the model, the procedure carried out to perform the econometric analysis and the interpretation of the results.

2.1 Data selection and data set construction

A large part of this thesis consisted in choosing the data to use and how to build the ideal data set through which perform the analysis. The data on zombie firms come from the Bureau van Dijk electronic library[2]. The data bank offers financial and chronological information on limited

[1] Also called the Bank Lending Channel

[2] https://neworbis.bvdinfo.com/

company, partnership, banks and insurance companies from all over the world. For each company Orbis provides time series balance sheet information, shareholders' data, identification and management information. The database allows to download information on firms that respected the parameters to be considered zombie firms. In particular, the definition followed in this study is given by by Adalet McGowan et al. (2017) of the Bank of International Settlement and it is called "broad definition"[3]. This method identifies a firm as zombie if its interest coverage ratio has been less than one for at least three consecutive years and if the company has at least 10 years old. Among thousands of firms in the euro area, this selection reduced the set to few hundreds.

In contrast with U.S. firms, European companies use bank financing as their principal funding source as only few bonds are issued in Europe. At the beginning, to obtain zombie firms relationship with private banks, the idea was to use the Thomson Reuters LPC's DealScan database. This provides a comprehensive coverage of the European syndicated loan market. Unfortunately, the database was not included in the set of data banks made available for students and it was not possible to use it as a trial. Therefore, the decision was to retrieve bank-firms relationship from the GlobalCapital website, part of the Euromoney Institutional Investor PLC group. Although not as precise, it supplies a database of historical information on the European syndicated loan market[4]. Hence, it was possible to identify the main arranger of the syndicated loan for the companies which information were accessible. This process further restricted the data set to 69 firms.

Once selected the companies comprehending the group of zombie firms and the banks acting as main arranger for each of them, aggregate lending data for each bank were downloaded. To retrieve these financial information the Moody's Analytics BankFocus database has been used. This is a comprehensive banking database used to identify, analyse and monitor banks and other financial institutions[5].

The next step was to quantify and collect data on central bank money transfers to the banking sector. Data on the amount of liquidity the European Central Bank has provided in its open market operations were retrieved. The Eurosystem's regular open market operations consist of one-week liquidity-providing operations (main refinancing operations, or MROs) as well as three-month liquidity-providing operations (longer-term refinancing operations, or LTROs). MROs serve to steer short-term interest rates, manage the liquidity situation and signal the monetary policy stance in the euro area, while LTROs provide additional longer-term refinancing to the financial sector. Moreover, in the last ten years, following the Great Financial Crisis and the eurozone Sovereign Debt Crisis, the ECB has also used non-standard monetary policy measures. Among these it is possible to recall: three-year LTROs, PELTROs – pandemic emergency longer-term refinancing operations, TLTROs - targeted longer-term refinancing operations, APP - asset purchases programme and PEPP - pandemic emergency purchase programme. Therefore, data on these aggregate operations were downloaded from the data warehouse of the ECB[6].

Finally, the Bureau van Dijk Electronic data bank was used to load data on zombie firms' total

[3] See Chapter 1 for more details
[4] https://www.globalcapital.com/data
[5] https://bankfocus.bvdinfo.com/
[6] https://sdw.ecb.europa.eu/

assets and the ECB data warehouse to get data on volumes of banking sector syndicated loans by country.

Figure 2.1: Panel Data Set Preview

year	ZF	credit	w_bankloan	log_moneysupply	log_zftotasset	log_countrysyndloans
2011	OUTOKUMPUOYJ	1	0.25846953	20.96813174	15.46934806	8.737131612
2012	OUTOKUMPUOYJ	1	0.27354088	21.05291701	16.08464227	8.781708986
2013	OUTOKUMPUOYJ	1	0.29374843	20.47065485	15.99287251	8.845057054
2014	OUTOKUMPUOYJ	0	0.21782138	20.27072642	15.67352582	8.73777346
2015	OUTOKUMPUOYJ	0	0.22457132	20.46372279	15.58604639	8.802071337
2016	OUTOKUMPUOYJ	0	0.21730861	20.74314787	15.60560197	8.874028123
2017	OUTOKUMPUOYJ	0	0.22796297	21.1017783	15.58825709	8.793763759
2018	OUTOKUMPUOYJ	0	0.24150538	21.02116281	15.60693664	8.928905412
2019	OUTOKUMPUOYJ	1	0.26722454	20.56264041	15.61358339	8.98506956
2020	OUTOKUMPUOYJ	0	0.25168973	21.630337	15.5728511	9.178643285
2011	SARASS.P.A.	1	0.01835046	20.96813174	15.23928301	11.78453151
2012	SARASS.P.A.	1	0.01859165	21.05291701	15.18667148	11.73084741
2013	SARASS.P.A.	0	0.01859543	20.47065485	15.15406609	11.55726766
2014	SARASS.P.A.	0	0.01762457	20.27072642	15.16669781	11.44096749
2015	SARASS.P.A.	1	0.01727723	20.46372279	15.01474495	11.40834242
2016	SARASS.P.A.	0	0.014862	20.74314787	14.87828287	11.48354815
2017	SARASS.P.A.	0	0.01410158	21.1017783	14.96518376	11.43580681
2018	SARASS.P.A.	0	0.0142081	21.02116281	14.90067246	11.53076538
2019	SARASS.P.A.	0	0.01255725	20.56264041	15.08638958	11.53113859
2020	SARASS.P.A.	1	0.01152886	21.630337	15.03047909	11.71492709
2011	BILFINGERSE	1	0.19914179	20.96813174	15.85927311	11.98670321
2012	BILFINGERSE	0	0.17113957	21.05291701	15.73974461	11.94000202
2013	BILFINGERSE	0	0.11032442	20.47065485	15.69214718	11.87583792
2014	BILFINGERSE	0	0.11794466	20.27072642	15.60084946	11.87263281
2015	BILFINGERSE	0	0.14002897	20.46372279	15.46118396	11.91386702
2016	BILFINGERSE	0	0.14597782	20.74314787	15.20651879	11.95133522
2017	BILFINGERSE	0	0.16373012	21.1017783	15.10206745	11.98371004
2018	BILFINGERSE	0	0.14919921	21.02116281	15.06139277	12.13989011
2019	BILFINGERSE	0	0.14845591	20.56264041	15.02590271	12.24064314
2020	BILFINGERSE	0	0.14407484	21.630337	14.99610214	12.27725778

Preview of the data set built to perform the analysis.

Source: Own elaboration

Regarding the data set, the chosen structure is panel data. Panel data are multi-dimensional data involving measurements over time. Like time series, they contain observations collected at a regular frequency, while similarly to cross-sectional data, they contain observations across a collection of individuals. As shown in *figure 2.1*, the individuals are the zombie firms (*ZF* variable), which data are collected over a time span of ten years, from 2010 to 2020. The variable *credit* identifies whether the firms has increased its amount of loans from banks in the respective year. Then, as already discussed, a variable that allows to link the flow of money supply from the central bank to zombie firms is included: *w_bankloan*. This is given by the main arranger's aggregate corporate loans over its total asset. This ratio acts as a standardizing factor that accounts for the turnover volume in order to isolate the impact of lending. Next, data from the ECB data warehouse were used as the measure of direct money supply to banks. The aggregate amount in each year, defined by the ECB as "Lending to euro area credit institutions related to monetary policies operations denominated in euro", is repeated for every zombie firms in the data set. This is given by two main type of operations: the first are the open market operations which include the main refinancing operations, the longer-term refinancing operations, fine-tuning reverse operations and structural reverse operations; the second are standing facilities which are available to eligible counterparties on their own initiative and that comprehend marginal lending facility and deposit facility. This amount is described by the variable *log_moneysupply* taken in logarithm for convenience. Finally, the same logarithmic transformation was applied to the total amount of assets of each zombie firm *log_zftotasset* and the total amount of syndicated loans granted by each zombie firm's respective country *log_countrysyndloans*.

2.1.1 Data analysis

It is now interesting to look at the characteristics of zombie firms in the data set. First, the analysis focuses on the sector composition. The main industry in terms of absolute number is property services, which accounts for almost a fifth of the whole data set. The property services industry is composed of a diverse range of sectors involved in the design, operation, servicing and sale of commercial and non-commercial buildings. The sector is at a key turning point in its business cycle and firms that are not able to adapt tend to suffer from poor financial performance. Then, there are several manufacturing sectors and construction. Caballero et al. (2008), argue that the less a sector is subject to international competition the larger the share of zombie firms, given that banks tend to find it more difficult to subsidize firms in sectors characterised by tight international competition. Generally, manufacturing is a sector strongly subject to international competition, while construction it is significantly less so. However, consistently with researches of the European Commission[7] the relative incidence of zombie firms is considerably high in the construction industry and even higher in the manufacturing sector. Finally, the financial services industry is present. This has been impacted by the low interest rate regime, the lack of profitable investment opportunities and the consequent increase in non-performing loans.

Figure 2.2: Zombie Firms' Industry Composition

Industry	Total	Relative Frequency
Property Services	12	18.18%
Industrial, Electric & Electronic Machinery	10	15.15%
Chemicals, Petroleum, Rubber & Plastic	7	10.61%
Metals & Metal Products	7	10.61%
Construction	6	9.09%
Banking, Insurance & Financial Services	4	6.06%
Others	20	30.30%

Industry composition of the zombie firms in the data set.
Source: Own elaboration

[7]See Issam et al., Fear of the Walking Dead? Incidence and Effects of Zombie Firms in Europe

Then, another table is displayed. The analysis now is focused on the national composition of the zombie firms in the data set and the corresponding banking sector's rating. The countries with the highest number of zombie firms are Italy and Germany accounting for more than twenty percent each. Despite the high presence of zombie firms in both countries, the numbers are more worrying in Italy where banks are perceived as less solid than the German ones. After them, Finland, Greece and France are the countries more represented in the data set. Among these, although the country has strengthened its financial stability, the Greek banking sector is still considered the more fragile internationally. The composition is quite consistent with the studies of the ECB [8] considered the economic weight of each country in the euro area. Yet, a higher number of Spanish and Portuguese zombie firms were expected in the data set.

Figure 2.3: Zombie Firms Country and Rating Composition

Country	Frequency	Banking Sector Rating
Italy	22.73%	BBB
Germany	21.21%	A
Finland	13.64%	A
Greece	13.64%	B
France	12.12%	A
Others	16.67%	BBB

National frequency and relative banking sector's rating of the zombie firms in the data.
Source: Bureau van Dijk electronic library and own elaboration

Next, the analysis concentrates on the ability of the data set to represent the banking sector in the eurozone. In particular, it is interesting to understand whether the selected banks acting as main arrangers, follow the euro area syndicated loan market. The data, coming from the European Central Bank data warehouse[9], are related to the aggregate syndicated loan market in the euro area from 2011 to the end of 2020. To statistically check the goodness of the data set, correlation levels are studied when the two series have the same time span. When comparing the two data sets annually, the correlation between the corporate lending data and the aggregate euro area syndicated loan market is above 80 percent[10]. The syndicated lending market in Europe received a major boost from the introduction of the Euro, but was also strongly influenced by the credit bubble inflated through the credit and eurozone crises. Indeed, the global impact of the credit crunch is visible in these data. Despite the prompt response of the ECB to the twin crisis that affected the eurozone at the beginning of the decade, the banking sector started reducing the amount of loans heavily in 2012. The decline stopped in 2013 and reached a plateau that protracted for a couple of years. During this period the euro area experienced a ultra-low inflation and interest rate regime in correspondence of expansionary unconventional monetary policies set by the European Central

[8]See Storz et al., Do we want these two to tango? On zombie firms and stressed banks in Europe
[9]https://sdw.ecb.europa.eu/. Series Key: BSI.M.U2.N.A.A20S.A.1.U2.0000.Z01.E
[10]See results in the appendix

Bank. Between 2014 and 2016 the ECB expanded its policy measures adding asset purchasing and commencing the quantitative easing. With the expansionary monetary policy, the ECB started buying assets from commercial banks, providing funds to the banking system and easing lending conditions. In 2020, the uncertainty caused by the pandemic has blocked funding to companies. The effect is pronounced especially at the beginning of the year when strict lock-downs where put into place by governments. The main effect has been on the supply side of the syndicated loan markets with banks asking for higher spreads due to deep uncertainty and reduction in the asset side of the balance sheet caused by the turmoil on financial markets. The ECB responded with the conduct of reverse repo operations and asset purchases in the secondary market, adjusting the quantity and consequently the price and liquidity of securities available. This operation changed the value of assets in banks and firms' portfolios. As a consequence, the ECB countermeasures were effective in lowering borrowing costs and stimulate lending. This allowed the syndicated loan market to recover and minimize its decline at the end of the year.

2.2 Econometric background

Before digging into the model, the chapter explores the theoretical foundations of the econometric analysis underneath it. First, the *probit* model is introduced. This nonlinear model is used to quantify the probability of an outcome to occur. The study discusses the reasons behind its use in contrast to the classic ordinary least squares (OLS) linear regression, the mathematical technique through which to build the model and how to measure the effects on the dependent variable. Then, the two-stages least-squares regression method is described. In particular, the review focuses on the issue of endogenous variables, the theoretical structures on which the model is based and the econometric approach used to derive the new estimator. Finally, the maximum likelihood estimation process is presented.

2.2.1 Probit model

When dealing with discrete outcomes, in econometric theory, the adoption of binary response models is considered. In these cases, the dependent variable y_i can take values 0 and 1. When examining the probability that y_i is one of the two, conditional to the information set Ω_i, a model that indicates its conditional probability has to be considered:

$$P_i = Pr(y_i = 1|\Omega_i) = E(y_i|\Omega_i) \tag{2.1}$$

This sort of problem does not allow to use the linear regression model, since it will not be able to impose the condition:

$$0 \leq E(y_i|\Omega_i) \leq 1. \tag{2.2}$$

Furthermore, if the dependent variable can only take the values 0 or 1, the disturbance term will follow a very strange pattern in the case of ordinary least squares regression. In fact, let's consider the ith observation in a OLS model. Since y, can only be 0 or 1, the ith disturbance term, ε_i can take on only one of the following two values:

$$\varepsilon_i = \begin{cases} 1 - X_i\beta & \text{if } y_i = 1 \\ -X_i\beta & \text{if } y_i = 0 \end{cases} \tag{2.3}$$

As a consequence, ε_i will not be normally distributed but will follow a discrete distribution. Econometric theory establishes that for β to be unbiased, in an ordinary least squares model, the expected value of the residuals must equal 0, while its variance must be constant to define the model as *homoskedastic*. In this case, the expected value of the residuals is:

$$E[\varepsilon_i] = P(-X_i\beta) + (1-P)(1-X_i\beta) = (1-X_i\beta)(-X_i\beta) + (X_i\beta)(1-X_i\beta) = 0 \tag{2.4}$$

While the variance of the disturbance terms is equal to:

$$E[\varepsilon_i]^2 = (-X_i\beta)^2(1-X_i\beta) + (1-X_i\beta)^2(X_i\beta) = (X_i\beta)(1-X_i\beta) = E[y_i][1-E[y_i] \tag{2.5}$$

The variance of the residuals depends on the values of the independent variables and therefore is not constant, violating the assumption of homeskedasticity. As a result, the OLS estimator will no longer be the minimum variance linear estimator.

Since the OLS should not be used when the dependent variable is discrete, a technique to convert the discrete dependent variable into a continuous one must be applied. One option is to substitute the probability of occurrence of a discrete event for the discrete event itself. Then, the independent variables used to quantify the probability measure and a functional form to be used in the model are determined. So, a constraint is imposed using the functional form:

$$P_i = E(y_i|\Omega_i) = F(\mathbf{X}_i\beta). \tag{2.6}$$

The new function $F()$ is a transformation function, with three main properties

$$F(-\infty) = 0, \quad F(\infty) = 1, \quad f(x) = \frac{dF(x)}{dx} > 0 \tag{2.7}$$

As a consequence, the new function $F()$ is non-linear. This entails that variation in the values of the independent variables $\mathbf{X}_i$ affect $E(y_i|\Omega_i)$ in a non-linear fashion, that is:

$$\frac{\partial P_i}{\partial x_{ij}} = \frac{\partial F(\mathbf{X}_i\beta)}{\partial x_{ij}} = f(\mathbf{X}_i\beta)\beta_j \tag{2.8}$$

Where B_j is the j-th element of β. Applying this concept, it is possible to compute the marginal effect in a binary response model.

One of the most widely used choices for the function $F()$ is the cumulative standard normal distribution

$$\Phi(X \le x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp(-X^2/2)dX. \tag{2.9}$$

From which the normal density function is obtained simply by taking the first derivative. When $F(\mathbf{X}_i\beta) = \Phi(\mathbf{X}_i\beta)$ it means that a probit model is specified. The probit model can be derived from a model involving an unobserved, latent, variable $y_i\star$, which is modelled as

$$y_i\star = X_i\beta + u_i, \quad u_i \sim N(0,1). \tag{2.10}$$

Only the sign of $y_i\star$ is observed. So that $y_i = 1$ if $y_i\star > 0$, else $y_i = 0$. Therefore, y can be thought of as the net utility associated with some action. The variance of u_i is not identified in the binary model since only the sign is observed. Hence, it is normalized to unity. Implying that $Pr(y_i = 1)$ is given by

$$P_i = Pr(y_i = 1) = Pr(u_i > -X_i\beta) = Pr(u_i \leq X_i\beta) = \Phi(X_i\beta). \tag{2.11}$$

For the actual estimation, the assumption that $y_1, y_2, ..., y_n$ is a sample of conditionally independent identically distributed draws from a Bernoulli distribution is made. Therefore, the cumulative density function is:

$$Prob(Y_1 = y_1, ..., Y_n = y_n) = \prod_{y_i=0}[1 - F(X_i\beta)] \prod_{y_i=1} F(X_i\beta) \tag{2.12}$$

From this CDF the log-likelihood function is derived as:

$$L(\beta; y, X) = \sum_{i=1}^{n}(y_i \log F(X_i\beta) + (1 - y_i)\log(1 - F(X_i\beta))) \tag{2.13}$$

Then, to maximize the product of the likelihoods $L(\beta; y, X)$ the maximum likelihood estimation is used. This technique allows to find the βs that maximize this expression.

2.2.2 Two-stages least-squares regression

The assumption that the errors and independent variables are uncorrelated in the linear regression model is often incorrect in reality. A large number of common situations involve variables that are unobserved or omitted in the equation. When this happens there is an endogeneity problem. In the endogeneity case, none of the proofs of consistency or unbiasedness of the least squares estimator will remain valid. Main causes of endogeneity are: omitted variables presence, measurement errors in the Xs, simultaneity problems and reverse causality. When these issues arise, it is convenient to use a different method to determine the causal link between the Xs and Y.

In this situation, the independent variables are partitioned in two sets: X_1 which is assumed to be the group of exogenous variables and X_2 which represents the endogenous ones in the model. Then, the matrix Z is introduced, representing another set of variables called instruments. This matrix follows two properties:

$$E[\varepsilon|Z] = 0, \quad E[ZX] \neq 0 \tag{2.14}$$

The instruments are *exogenous*, since they are uncorrelated with the disturbance and present a certain degree of correlation with the independent variables X. The matrix Z is made up of two set of variables $Z = [X_1, Z_2]$. This distinction allows to build a reduced structural form of the model to better understand the connection between its elements:

$$\begin{cases} y = X\beta + \varepsilon \\ X = Z\Gamma + u \end{cases} \tag{2.15}$$

Starting from the reduced from of the model the equation for β and Γ can be derived:

$$\begin{aligned} y &= (Z\Gamma + u)\beta + \varepsilon \\ y &= Z\Gamma\beta + u\beta + \varepsilon \\ y &= W\beta + v \end{aligned}$$

Where $W = Z\Gamma$ and $v = u\beta + \varepsilon$. Using the OLS estimator of β in the first equation it becomes:

$$\begin{aligned} \hat{\beta} &= (W'W)^{-1}W'y \\ \hat{\beta} &= (\Gamma'Z'Z\Gamma)^{-1}\Gamma'Z'y \end{aligned}$$

But Γ is unknown. It can be retrieved by estimating $\hat{\Gamma}$ using (2.15) and substituting it into the previous equation:

$$\begin{cases} \hat{\Gamma} = (Z'Z)^{-1}Z'X \\ \hat{\beta} = [(X'Z)(Z'Z)^{-1}(Z'Z)(Z'Z)^{-1}Z'X]^{-1}[(X'Z)(Z'Z)^{-1}Z'y] \\ \hat{\beta_{IV}} = [X'Z(Z'Z)^{-1}Z'X]^{-1}X'Z(Z'Z)^{-1}Z'y \end{cases} \tag{2.16}$$

Knowing that the form $Z(Z'Z)^{-1}Z = P_z$ is called the projection matrix and that P_z is idempotent, the fitted value $\hat{X}$ of a regression of X on Z can be obtained.

$$\begin{aligned} \hat{\beta_{IV}} &= [X'P_zX]^{-1}X'P_zy \\ \hat{\beta_{IV}} &= [\hat{X}'\hat{X}]^{-1}\hat{X}'y \end{aligned}$$

In words, the method entails a two-steps process to estimate the $\hat{\beta}$s using instrumental variables. In the first step the X is regressed on Z to retrieve $\hat{X}$, in the second one y is regressed on $\hat{X}$ to obtain $\hat{\beta_{IV}}$.

2.2.3 Maximum likelihood estimation

Now that the building blocks of the model have been described, the final step is to use the best possible method to estimate the parameters. The technique adopted in this study is the *Maximum Likelihood Estimation* (MLE). The general principle behind the MLE method is to find the estimators of the parameters that make the considered sample most probable. In other words, knowing the parameter's values is sufficient to obtain a representation of the observed random variables.

First, to obtain the probability of a particular sample, its joint density function has to be recalled. Any likelihood function can be derived. For simplicity, suppose to have the normal distribution with two parameters $\theta = \mu, \sigma$, the mean and the standard deviation, to estimate[11].

$$f(x_1, x_2, ..., x_n|\theta) = \prod_{i=1}^{n} f(x_i|\mu, \sigma) = [\frac{1}{\sqrt{2\pi\sigma_i^2}}]^2 \prod_{i=1}^{n} \exp - \frac{(x_i - \mu)^2}{2\sigma_i^2} \tag{2.17}$$

Equation (3.17) is the likelihood function, that has to be maximized. To that end, taking its logarithm will make calculation simpler thanks to the conversion from products to sum and the nice properties it respects. Hence the log-likelihood function can be written as:

$$\ln \mathscr{L}(\theta|x_1, x_2, ..., x_n) = \ln \prod_{i=1}^{n} f(x_i|\mu, \sigma) = -\frac{n}{2}\ln(2\pi\sigma^2) + \sum_{i=1}^{n} -\frac{(x_i - \mu)^2}{2\sigma^2} \tag{2.18}$$

Now, taking the first derivative with respect to the two parameters will give the argmax of the likelihood function which coincides with the maximum of the original function since it is monotonically increasing. Therefore, differentiating with respect to the two parameters and equating to zero it is possible to find the MLEs:

$$\frac{\partial}{\partial\mu} \ln \mathscr{L}(\theta|x_1, x_2, ..., x_n) = 0 \rightarrow \mu = \sum_{i=1}^{n} \frac{x_i}{n}$$
$$\frac{\partial}{\partial\sigma} \ln \mathscr{L}(\theta|x_1, x_2, ..., x_n) = 0 \rightarrow \sigma = \sum_{i=1}^{n} \frac{(x_i - \mu)^2}{n}$$

The MLE method is widely used in econometric applications since it has many advantages: is the most efficient unbiased estimator and when the likelihood function has a unique global maximum is also consistent, meaning that as the sample size increases, $n \rightarrow \infty$, the estimator converges in probability to the true value of the parameter by uniform law of large number[12]. Furthermore, it allows to use a more robust estimation method called *Quasi Maximum Likelihood Estimation* (QMLE) which is implemented when the joint distribution could have been misspecified.

2.3 Model outline

The model presented in this section takes inspiration from a well-known paper written by Gabriel Chodorow Reich (2014)[13]. In his study, the author analyses the effect of the banking lending

[11] In this case, the sample of random variables is normally distributed $X_i \sim \mathscr{N}(\mu, \sigma)$

[12] The Uniform Law of Large Number states that $E_n[\mathscr{L}(\theta)] \rightarrow E_{\theta_0}[\mathscr{L}(\theta)]$ meaning that, for each value of θ the sample average of the log-likelihood evaluated in this parameter converges to the population expectation of the log-likelihood function evaluated in θ

[13] See: Gabriel Chodorow Reich, "The employment effects of credit market disruptions: firm-level evidence from the 2008–9 financial crisis"

frictions on the real economy, following the Great Financial Crisis. In particular, combining information on banks behaviour with corporate data in the U.S., the author finds a link between the credit crunch subsequent to the Lehman Brothers bankruptcy and the employment decline at small and medium firms. The econometric strategy carried out by the author entailed the use of a two-stages least-squares regression via a probit model. More specifically, he expresses the probability of obtaining a new loan or a positive modification as a function of some explanatory variables. To do so, he uses a two-stage instrumental variable approach, where he first regresses the change in loan supply on the instruments, obtaining a fitted value for the loan variation. Then, trying to capture the component of the regressors that was influenced by the losses banks have suffered during the crisis, he regresses the first-stage dependent variable on the probability of obtaining a new loan or a positive modification of it.

Thanks to the structural similarities between this work and the paper of Chodorow Reich, the decision to apply the same approach was immediate. In particular, the model aims to understand the consequences expansionary monetary policies have had on the likelihood of zombie firms to obtain credit. Central banks affect loan supply directed to firms through their open market operations, purchasing securities from commercial banks. These operations are put into place through the bank lending channel[14] and increase the amount of cash reserves each bank owns. By altering the credit supply, they encourage banks to grant more loans and further stimulate investments. In a recession setting, however, researchers have seen that distorting mechanisms show up and part of this liquidity is misallocated to unproductive firms. A further theoretical assumption must be considered to validate this reasoning. The modelling strategy of this study requires firms and lenders to form commercial relationships, alternatively zombie companies could costlessly switch to borrowing from other banks. The creation of these relationship is justified by the formation of economic advantages in remaining with the same lenders[15].

To model this concept, the money supply directed to banks is used as instrument and the aggregate corporate loan volume of each bank as endogenous variable. The second stage is the probit model, namely, the link between the fitted value of credit supply and the likelihood of zombie firms to obtain credit. Therefore, the resulting regression explains how the money supply, through the bank lending channel, affects the probability of zombie firms to receive new loans. Now, it is possible to write the equations that express this probability as a function of the other explanatory variables:

$$\begin{cases} Credit_{i,t} = \Phi(\beta_0 + X_{i,t}\beta_1 + \hat{Y}_{i,t}\beta_2 + \varepsilon_{i,t}) \\ \hat{Y}_{i,t} = \gamma_0 + X_{i,t}\gamma_1 + Z_t\gamma_2 + v_{i,t} \end{cases} \tag{2.19}$$

where $Credit_{i,t}$ is an indicator variable taking value one if the zombie firms i has increased its amount of debt towards banks in the period between time t and $t-1$ and zero otherwise. The $X_{i,t}$ is a matrix of exogenous variables comprehending the logarithms of the total amount of asset owned by zombie firm i at time t and the amount of syndicated loans granted in the country of firm i at

[14]See Apergisa, et al. The Bank Lending Channel and Monetary Policy Rules: Further Extensions (2012)

[15]See Gabriel Chodorow-Reich, the employment effects of credit market disruptions: firm-level evidence from the 2008-9 financial crisis

time t. Then, $Y_{i,t}$ is the matrix of endogenous variable[16] represented by bank i total corporate loans standardized by its total asset value at time t. In this way it is possible to control for the size of each banks. Then, the vector Z_t is the instrumental variable, where the instrument is given by the logarithm of the total amount of lending to euro area credit institutions related to monetary policies operations for each firm i at time t. Finally, $\varepsilon_{i,t}$ and $v_{i,t}$ describe the error terms.

2.4 Implementation

The software used to implement the analysis is Stata. The programming language has revealed to be the most ideal one since it was possible to estimate parameters and statistics by typing very few commands[17]. Stata propose a large number of models from which to choose, however there is no specific command for the two-stages least-squares regression probit model with panel data. Therefore, as discussed in a couple of papers[18], the best alternative is to select the two-stages least-squares probit model and add the option of clustering on the basis of the identifying variable to account for the panel feature.

Therefore, the model used in this analysis is the *ivprobit*. This model is used for binary dependent variables where one or more covariates are endogenous and it applies the maximum likelihood method to estimate the parameters. Formally the model is:

$$\begin{aligned} y\star_{1i} &= y_{2i}\beta + x_{i1}\gamma + u_i \\ y_{2i} &= x_{1i}\pi_1 + x_{2i}\pi_2 + v_i \end{aligned} \tag{2.20}$$

This is a recursive model since y_{2i} appears in the equation for $y\star_{1i}$, while $y\star_{1i}$ is not present in the other equation. There are a number of assumptions, first of all $(u_i, v_i) \sim \mathcal{N}(0, \sigma)$, where $sigma_{11}$ is normalized to one to identify the model; as already stated in the econometric background section, errors must be independent with the instrument and the endogenous variable and instrument must be correlated. The vectors β and γ are structural parameters and π_1 and π_2 are matrices of reduced-form parameters. Furthermore, $y\star_{1i}$ is not observable, instead what is noticeable is that:

$$y_{1i} = \begin{cases} 0 & \text{if } y\star_{1i} < 0 \\ 1 & \text{if } y\star_{1i} \geq 0 \end{cases} \tag{2.21}$$

First, let's examine the data set. The last line describes the identifying variable *ZF1*, this is the product of the "encode" command. In fact, since the group of zombie firms is identified by names, which is read by Stata as string, it is necessary to convert it to a numeric variable. As already discussed, there are 66 firms for a time span of ten years. Then there is the dichotomic variable *credit* which represents the dependent variable of the probit model, the endogenous variable *w_bankloan* standardized by the total amount of asset of each bank to control for their size and the instrument

[16] A vector in this case, since there is only one endogenous variable

[17] See in the appendix Stata commands

[18] Whitney K. Newey, Efficient estimation of limited dependent variable models with endogenous explanatory variables(1986) ; Rivers et al., Limited Information estimators and exogeneity tests for simultaneous probit models (1988)

log_moneysupply measuring the log of ECB's lending to euro area credit institutions via monetary policies operations. Finally, the *log_zftotasset* and *log_countrysyndloans* are the exogenous variables.

Figure 2.4: Data set overview

Variable	Obs	Mean	Std. dev.	Min	Max
year	660	2015.5	2.87446	2011	2020
ZF	0				
credit	660	.3348485	.4722954	0	1
w_bankloan	660	.18229	.1816247	.00028	.7945231
log_moneys~y	660	20.82852	.384322	20.27073	21.63034
log_zftota~t	660	12.10498	1.665871	8.647695	16.18404
log_countr~s	660	10.8751	1.187827	8.737132	12.27726
ZF1	660	33.5	19.06482	1	66

Overview of the data set used to perform the econometric analysis.

Source: Stata and own elaboration

Then, it is possible to proceed with the estimation of the model. The probit model with endogenous regressors shows first the value of the *pseudo log-likelihood*. Since the data are clustered with respect to the single firm, they are not anymore independent and identically distributed. Therefore, Stata writes down the pseudo-likelihood which looks exactly the same as how the likelihood would look for the i.i.d. case. The *Wald chi2* is the Wald Chi-Square statistic. It is used to test the hypothesis that at least one of the predictors' regression coefficient is not equal to zero. The number in the parenthesis indicates the degrees of freedom of the Chi-Square distribution used to test the Wald Chi-Square statistic and is defined by the number of predictors in the model (three). *Prob > chi2* is the probability of getting a Wald test statistic as extreme as, or more so, than the observed statistic under the null hypothesis; the null hypothesis is that all of the regression coefficients are simultaneously equal to zero. In other words, this is the probability of obtaining this chi-square statistic (255.85) or one more extreme if there is in fact no effect of the predictor variables. This p-value is compared to a specified alpha level, the willingness to accept a type I error, which is typically set at 0.05 or 0.01. The small p-value from the Wald test, lead to conclude that at least one of the regression coefficients in the model is not equal to zero. For what concerns the *Coefficient* values, the interpretation is not straightforward. The probit model follows the cumulative distribution function of the standard normal, therefore the coefficient represents the correspondent variation in the z-score of probability($Credit = 1$) following an infinitesimal change in the independent variable. However, this does not translate in a constant effect on the dependent variable variation. In this case, the marginal impact of changing a variable is not constant. In fact, the probability attributed to a one-unit increase in a given predictor is dependent both on the values of the other predictors and the starting value of the given predictors. Yet, there are limited ways in which the individual regression coefficients can be interpreted. A positive coefficient means that an increase in the regressor leads to an increase in the predicted probability. Then, there are the *Robust standard errors*

Figure 2.5: Ivprobit results on Stata

```
Probit model with endogenous regressors              Number of obs =     660
                                                     Wald chi2(3)  = 255.85
Log pseudolikelihood = -193.20694                    Prob > chi2   = 0.0000

                                   (Std. err. adjusted for 66 clusters in ZF1)
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
w_bankloan	5.649884	.4426609	12.76	0.000	4.782285	6.517483
log_zftotasset	.08279	.0580092	1.43	0.154	-.0309059	.1964859
log_countrysyndloans	.224723	.1026793	2.19	0.029	.0234753	.4259707
_cons	-4.539229	1.192659	-3.81	0.000	-6.876797	-2.20166
corr(e.w_bankloan,e.credit)	-.989363	.0138225			-.9991741	-.8705506
sd(e.w_bankloan)	.173335	.0145746			.1469989	.2043893

```
Wald test of exogeneity (corr = 0): chi2(1) = 16.03       Prob > chi2 = 0.0001
```

Results of the Ivprobit model on Stata.
Source: Stata and own elaboration

of the individual regression coefficients, used in both the calculation of the z test statistic and the confidence interval of the regression coefficient. The *z-test statistic* is the ratio of the coefficients to the standard errors of the respective predictor. The z-value follows a standard normal distribution which is used to test against a two-sided alternative hypothesis that the coefficient is not equal to zero. Next, the $P > |z|$ is the probability that the z test statistic (or a more extreme test statistic) would be observed under the null hypothesis that a particular predictor's regression coefficient is zero, given that the rest of the predictors are in the model. For a given alpha level, this determines whether or not the null hypothesis can be rejected. In this specific case, only the control variable textitlog_zftotasset has an associated p-value that leads to reject the null hypothesis. The variable of interest *w_bankloan*, already fitted considering the instrumental variable *log_moneysupply*, is statistically different from zero at all the levels of alpha. This indicates that aggregate lending has a positive effect on the likelihood of zombie firms to obtain credit. Finally, at the bottom of the output, there is the Wald test of the exogeneity of the instrumented variables, this suggests to reject the null hypothesis of no endogeneity.

As already discussed, the probit model poses some problems in the interpretation of coefficients. The main issue arises from the fact that the effect on the dependent variable is not constant but depends on all the regressors at the same time. Another way of saying the same thing is that:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \qquad Y = \Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)$$

$$\frac{\partial Y}{\partial x_i} = \beta_i \qquad \frac{\partial Y}{\partial x_i} = \beta_i \phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)$$

where the first column describes the effect in a linear model and the second in a probit model. To calculate the marginal effect of a single regressor, the first option is to set all the variables to their means. Then it is possible to estimate the marginal effect at a specific point $x^\star$, which is usually the mean. A different approach is to use the average partial effect which consists in an estimation of a population-averaged marginal effect.

$$\frac{\beta_i}{N}\sum_{i=1}^{N} f(x_i\beta) \tag{2.22}$$

is the average partial effect of x_i when x_i is continuous. Another important issue is whether the variable is discrete (i.e. categorical) or continuous. In particular, as discussed by Long (1997) and Cameron et al. (2010)[19], the computation and interpretation of marginal effects differ in these two cases. When the independent variable is binary, the marginal effect measures the discrete change (from 0 to 1), while when the variable is continuous the marginal effect represents the instantaneous rate of change. When dealing with continuous variables, there is no guarantee that a bigger increase in the independent variable would automatically produce a proportional increase in the probability of the dependent variable to occur. This effect is caused by the non-linear relationship between the two variables.

Figure 2.6: Results of margins analysis on Stata

```
Average marginal effects                                Number of obs = 660
Model VCE: Robust

Expression: Average structural function probabilities, predict(pr)
dy/dx wrt:  w_bankloan log_zftotasset log_countrysyndloans
```

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
w_bankloan	13.87581	8.93459	1.55	0.120	-3.635667	31.38728
log_zftotasset	.2033277	.2044633	0.99	0.320	-.1974131	.6040684
log_countrysyndloans	.5519075	.3955042	1.40	0.163	-.2232664	1.327081

Calculation of the marginal effects of dependent variables on the probability of obtaining credit.
Source: Stata and own elaboration

Figure 2.6 shows the results using the average marginal effect method. The independent variables are all continuous, thus the margins are interpreted as the increase (decrease) in the probability of obtaining credit when one of the regressor is changed by a very small amount. Looking at the values it is possible to give an interpretation of the effect each of them has on the dependent variable. In particular, the parameter of interest is *w_bankloan* which is 13.88. This can be interpreted as, when the amount of aggregate loans divided by its asset increases by a very small amount (.001) the likelihood of a zombie firm to obtain credit increases by .001 * 13.88 = .0139. Therefore, it is possible to infer that loan supply does affect the likelihood of a zombie firm to obtain credit. As a consequence, monetary policy, providing resources to the banking sector, is a key contributor of this mechanism. Policymakers should therefore consider that, while expansionary monetary policies support aggregate demand, employment and investment in the short run, adverse effects in the medium and longer-term occur too. In particular, these policies create the conditions

[19]Long 1997, Long and Freese 2003 & 2006 & 2014, Cameron & Trivedi's "Microeconomics Using Stata" Revised Edition, 2010

for the proliferation of zombie firms, which in turn increase resources' misallocation and decrease aggregate productivity. Should this effect be strong enough to reduce growth, it could even have a reverse causality effect depressing interest rates further. The statistical significance of predictive margins is usually of no importance in any analysis, since the p-value in that row is a test of the null hypothesis that the predicted probability is zero. Similarly, the interpretation that can be given to the other two margins is that both the size of each zombie firms and the aggregate syndicated loans in each country have non-substantial impact on the probability of the dependent variable to occur.

Consistently with its general objective, this analysis presents a number of limitations and assumptions. First, zombie firms in the data set are most probably only a fraction of the actual number in the euro zone. The main issue here is that very few financial information are available on small and medium enterprises in Europe. In fact, the vast majority of studies on zombie firms use data on listed companies which are in general larger and older. At the same time, the impossibility to use the Thomson Reuters LPC's DealScan database implies a significant reduction in the number of zombie firms of which syndicated loans information are available. Finally, differently from the paper written by Chodorow-Reich (2014), this work adopts the use of aggregate instruments and endogenous variables instead of "bank-specific" ones. Therefore, this analysis aims to provide an innovative framework and a general guideline on the mechanism that cause monetary policy to affect zombie firms. Further studies may instead explore the individual relationship between central banks' tools, banks and zombie firms.

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Chapter 3

The COVID-19 Pandemic Crisis and Zombie Firms: A Renewed Challenge

The severe respiratory syndrome SARS-CoV-2 and the disease it causes (COVID-19) were officially identified first in December 2019 in Wuhan, China. The virus quickly spread across the globe evolving into a health pandemic and causing severe disruptions in economic activities due to the measures taken to curb its expansion. The COVID-19 pandemic can be considered the largest shock of the post-crisis financial system to date. In fact, the health crisis caused by the virus and its unparalleled economic consequences have been felt worldwide, impacting almost any country and simultaneously affecting demand, supply and financial conditions. The crisis is different from any other previously experienced. First, it is a global macroeconomic shock of unprecedented magnitude. The global gross domestic product (GDP) in 2020 has decreased by 3.2%, according to the International Monetary Fund, with an output loss of almost three trillion dollars respective to 2019. Second, the crisis is characterized by great uncertainty. At the beginning, the ambiguity was caused by the unknown duration and intensity of the shock, the doubt about the effectiveness of the containment measures and the possible developments of the health crisis. Afterwards, the economic conditions have been closely tied with the progressive vaccine rollout and the control over the new variants of the virus. Third, the crisis has implied a new and different role for economic policies. In normal crises, policymakers try to encourage economic activity by stimulating aggregate demand as quickly as possible. This time, the crisis is to a large extent the consequence of needed containment measures. In the wake of the outbreak of the virus, this made stimulating activity more challenging and often in contrast with healthy measures.

The global economy has started a slow recovery since the "Great Lockdown", with continuous periods of growing health risks and social and economic restrictions alternated with gradual reopening of businesses and activities. However, the rapid production and distribution of several vaccines against the disease has set the basis for a return to normality. Nevertheless, large divergences are already visible among advanced and emerging economies. Around 70 percent of the population in advanced economies has been fully vaccinated, compared with less than half that number in emerging market economies and a tiny fraction in low-income countries. Vaccine access represents the principal discretion element that splits the global recovery into two blocs:

those that have started and are planning to further normalize the economy later this year (almost all advanced economies) and those that will still face potential resurgent infections and rising death tolls. At the same time, a further source of divergence is the fiscal and monetary policy support[1]. While advanced economies are not interested yet in decelerate their stimulus efforts, many emerging economies are looking to rebuild fiscal buffers and others such as Brazil, Hungary, Mexico, Russia, and Turkey, have also begun monetary policy normalization to contrast upward price pressures.

The chapter discusses the effects of the COVID-19 pandemic crisis on financial markets and the real economy, the response strategy structured by governments and central banks and the effects on the phenomenon of zombie firms. In particular, the first section presents the repercussions the health crisis had on financial markets in the first and second quarter of 2020. To complete this discussion, the monetary policy response is examined with a particular emphasis on similarities and differences between advanced and emerging economies. Also, policies directed to avert the potential financial crisis and support aggregate demand are considered, with a distinction based on the scope and the type of instrument used. Next, the chapter explores the impact the COVID-19 crisis may have on firms, both in the short and the long term; the overall current financial situation and the factors that may stimulate zombie lending. The last section, instead, reviews the principal measures discussed recently to prevent the increase in zombie firms and how to calibrate fiscal and monetary policy in this sense.

3.1 Monetary policy response to the COVID-19 pandemic

The lockdowns imposed to curb the COVID-19 pandemic have prompted unprecedented limits to the normal economic activity. The containment and social distancing measures taken to curb the spread of the virus have caused a sudden and sharp reduction of both demand and supply for many goods and most services. Alongside, the COVID-19 pandemic has led to a large re-pricing and re-positioning in global financial markets. Sudden increase in risk aversion, caused by the continued downward revisions of economic growth expectations, combined with high uncertainty about the future development of the pandemic, have led to experience extreme volatility in equity and other markets for risky assets, capital outflows from emerging markets and sharp moves in foreign exchange rates. Consequently, several stress metrics reached historical records. Funding markets have been under strain amid extreme demand for cash and near-cash assets, with impaired activity and price discovery, including in some markets that are usually highly liquid.

Regarding policymakers' response, their reaction to the economic issues caused by the pandemic was prompt and on a large scale. For the first time in decades, governments and central banks coordinate their fiscal and monetary response, providing large stimulus both to the real and financial sector. The objective in advanced economies (AEs) was twofold. On the one hand, the immediate problem for monetary policy was to stabilise financial markets to prevent a new global

[1]Especially considering the additional fiscal support in the United States with the proposed American Jobs Plan and American Families Plan and in the European Union with the Next Generation EU

financial crisis. Thus, central banks deployed asset purchases and liquidity provisions as key instruments to avoid financial markets to freeze. On the other hand, when it appeared clear that the impact on households and the corporate sector would have been substantial and prolonged, central banks decided to override their general mandate to provide a cushion to the contraction in real activity. To do so, monetary policy ensured the provision, under favourable conditions, of credit to the private sector[2]. Instead, the reaction of emerging market economies and their central banks was linked to the specific issues and factors faced by their financial systems. Looking at key macroeconomic aspects, most emerging market economies (EMEs) found themselves at a relatively low point of the business cycle, with aggregate demand generally below potential. The main issue in financial markets was the rapid appreciation of the US dollars that characterizes period of economic downturns, however the wide and vigorous actions taken immediately by central banks in AEs helped containing the strengthening of the dollar. Consequently, central banks in EMEs were free to focus their monetary policies on domestic objectives, such as support of aggregate demand while the outflows of capital and currency depreciation was relatively limited[3].

3.1.1 The immediate impact on financial markets

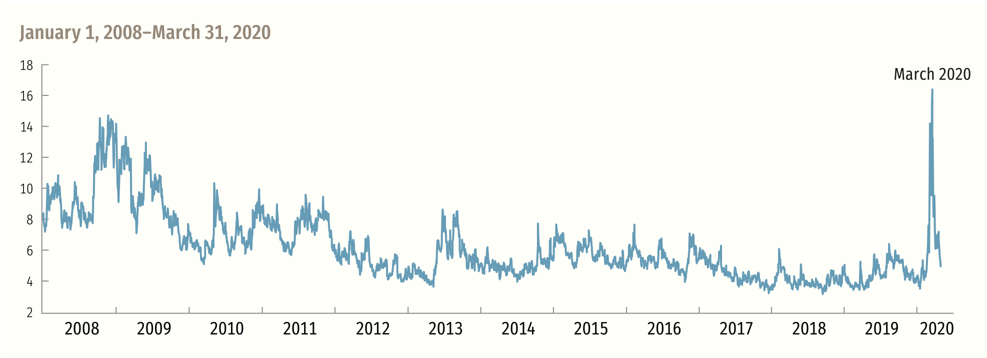
The corporate bond market was the epicentre of the financial turmoil. In particular, in the beginning months of March and April 2020 this market was strongly affected by large increase in corporate spreads. The stress began in sovereign debt markets and quickly spilled over into other credit markets such as commercial paper, asset-backed securities, mortgage backed securities and high-yield bonds. The panic in the bond market was manifested with sudden hikes in spreads and a reduction in liquidity. Oddly, the fast increase in spreads of corporate bonds was not linked with a similar increase in credit default swaps (CDS), so the majority of it must have been driven by sources different than the increase in credit risk. In fact, the main cause of the large stress was the urgent demand for liquidity due to the raising uncertainty about the real effect of the virus. The depressing effect on liquidity in the corporate bond market aroused from demand for cash by institutional investors, such as mutual funds and by larger constraints faced by financial intermediaries. Both these factors contributed to put further pressure on liquidity and reduce the prices of assets beyond what the increase in credit risk would have normally implied. Among the changes in liquidity attributed to the role of financial intermediaries an important effect is studied by Kargar et al (2021). In particular, they distinguish between risky-principal trades, where the dealers purchase the asset immediately, holding it until the find of a new buyer; and agency trades, where the sellers are obligated to retain the asset until the dealers find a new buyer. They show that the fees related with risky-principal trades raised dramatically in the height of the crisis, pushing clients to switch to the less-preferred agency trade. Therefore, the way liquidity was compromised is reflected not only in larger costs but also in slower speed.

Problems arose almost immediately also in the US Treasury market, globally considered a safe haven in times of markets uncertainty. Normally, demand for Treasury securities would drive yields

[2]See: Cavallino and De Fiore (2020)
[3]See: Aguilar and Cantú (2020)

down and prices up. However, after a short reduction in yields, the US bond market experienced a sell-off and a sharp increase in long-term yields in March. At the same time, euro area sovereign spreads widened substantially. This effect can be seen also by looking at the correlation between stock prices and Treasury yields which in general is positive. In this occasion, even when stock prices fell, Treasury bond rose consistently. The abnormal correlation suggests that the Treasury markets were becoming distorted. The different change in 10-year Treasury yields was caused, in part, by market participants who were in desperate need for cash, thus they turned to sell Treasury bonds. Another sign that the Treasury bond market was distorted come from the bid-ask spread. Usually, Treasury bonds bid-ask spreads are narrow, in the range of 1 to 3 basis points. This suggests that the market is deep and liquid and that Treasury bonds can be bought or sold promptly with low transaction costs. In specific situations, when fixed-income markets are under pressure, it happens that these mechanisms may break down. The market showed normal behaviour in February but quickly jumped up in March to 13 basis point and remained elevated until the end of March. Finally, it is possible to infer elevated stress levels from the Treasury market volatility measure, which increased sharply. Volatility in Treasury futures markets, as measured by the

Figure 3.1: TVYIX over time



TVIX index, representing volatility in the Treasury futures market.
Source: Chicago Board Options Exchange data bank

TYVIX index, which in March 2020 reached levels exceeding those seen during the global financial crisis (*figure 3.1*). As discussed before, the dislocation in the Treasury market quickly spread to the short-term credit markets (interbank lending, commercial paper and short-term municipal debt markets). In normal times, all these instruments are considered high-quality investments and sufficient to maintain appropriate levels of liquidity. During March, however, investors' perception of what constituted liquid investments were far narrower, only true "cash securities" that mature overnight were acceptable and spreads rose quickly all over these markets.

Stock markets around the globe underestimated COVID-19 developments in the first moment, probably because of the uncertainty and opaqueness that characterized the first outbreak in China. The situation changed, however, over the third week of February, when world stock markets began falling and continued to decline through the third week of March. Overall contractions in stock prices varied by country[4]. Looking at the US stock market, the drop experienced between February

[4]for example, Germany and France saw larger overall declines while Japan experienced only a small overall reduction

and March was astonishingly swift, even compared to what seen during the GFC (*figure 3.2*). By the 23 of March, the index hit a nadir, 34% below its peak in February. This sudden drop occurred in only 23 trading days. By comparison, during the global financial crisis, it took the S&P 500 index one year to fall 34% from its all-time high in October. The swift drop in the

Figure 3.2: S&P 500 decline in the COVID-crisis and in the GFC

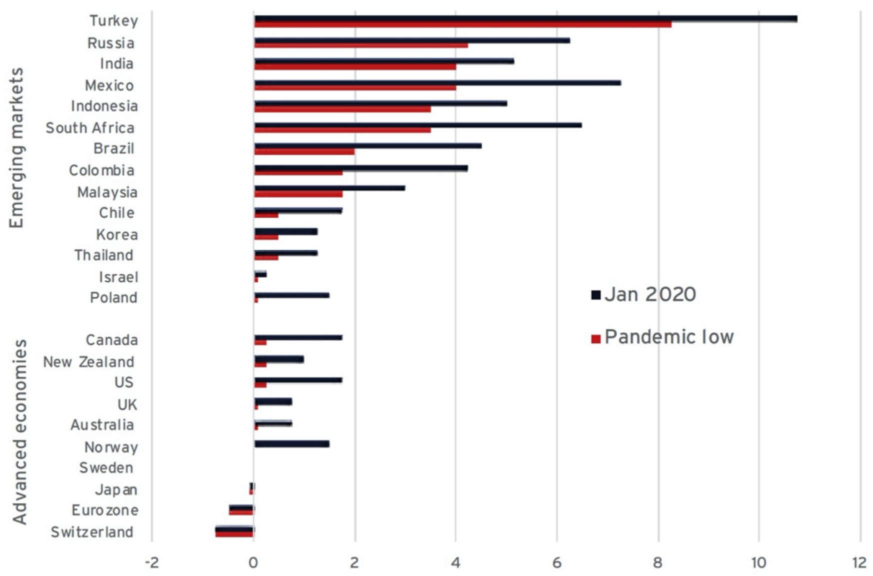
Trading days needed to the S&P 500 to fall 34% during the COVID-crisis and the GFC. The index is scaled to 1.0 on stock market peak on October 9, 2007, for the global financial crisis and on February 19, 2020, for the COVID-19 crisis.
Source: The Investment Company Institute, "The Impact of COVID-19 on Economies and Financial Markets"

U.S. stock market value produced also some of the largest one-day decline after the World War II. Three different days in March 2020 entered among the 20 days largest drop in the S&P 500. The index has also seen temporarily stop due to markets hitting limit-up or limit-down circuit breakers. This insight is important to appreciate the scale of COVID-19 on financial markets and to understand the connection with market dislocations seen in that period. Sharp drops in asset prices in fact, force investors to adjust their positions, compensate margin and collateral calls or deleverage. Economic and health uncertainties weighted strongly on investor psychology, leading to increased risk aversion and confusion. A measure of the fear on markets, the VIX index, which assesses the implied volatility of stock prices, jumped to levels exceeding those seen during the GFC. Afterwards, since mid-March volatility receded, but nevertheless remained elevated relative to historical averages, spiking from time to time with jumps reflecting upticks in the numbers of new COVID-19 cases or the re-imposition of containment measures and health mandates.

3.1.2 The response of monetary policy

At the break of the COVID-19 Pandemic, central banks were still trying to understand how to sustain inflation a decade after the Global Financial Crisis. In a situation where a low interest rate environment was necessary to stimulate dormant inflation, the swiftness and strength of the economic and financial deterioration caused by the pandemic, triggered an unprecedent response in terms of size, speed and scope by central banks. The exogenous shock caused a non-standard global recession, differently from the GFC which was triggered by endogenous financial excesses. Hence, this recession required a different reaction. Central banks had to confront with the challenge of stabilising the financial markets and support the real economy. Therefore, short-term rates, which were already at record low levels in most advanced economies, were further decreased. Also emerging markets saw broad interest rate cut, with rates even approaching zero in a number of countries such as Chile, Israel, Korea and Poland (*figure 3.3*). Although it was clear that fiscal and health policies would act as key countermeasures in fighting the pandemic and generating a recovery, monetary policy still had a critical role to play as markets froze, capital outflows from emerging markets started, and economic activity shuttered. Central banks immediately resorted to the instruments adopted in the wake of the GFC, reviving measures and facilities that had previously been developed. Then, new set of programmes were introduced to tailor the support to this peculiar crisis with instruments designed for specific segments of the economy.

Figure 3.3: Central banks policy rates: before and after the pandemic



Difference in short term interest rates set by central banks in emerging and advanced economies before and after the COVID-19 pandemic.
Source: CEPR PRESS “Monetary Policy and Central Banking in the Covid Era”

Central banks tools to respond to the pandemic can be divided into four categories, according to a new book edited by the CEPR press[5]: rate cuts and forward guidance, asset purchases, liquidity provision and credit support and regulatory easing. Most central banks, in fact, adopted a wide range of instrument that comprehended these four broad categories. Interestingly, all these tools: cutting rates to zero or negative, using forward guidance, buying assets and adopt more generous lending programmes can now be considered as more common instrument for monetary policy, ending de facto, the traditional distinction between conventional and unconventional policies. Not

[5]See: Bill English, Kristin Forbes and Angel Ubid; Monetary Policy and Central Banking in the COVID Era

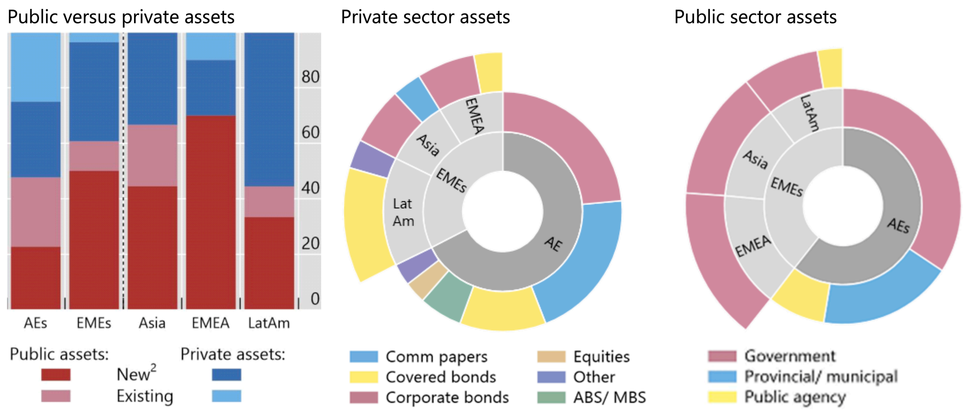
only it is expected that central banks will continue to use these programmes in the future, but also emerging economies, which had always relied on adjustments to policy rates and foreign exchange intervention, started using asset purchases and other new tools without provoking a negative market reaction.

Soon after the outburst of the COVID-19 pandemic, many central banks in advanced economies quickly cut their interest rate to lower funding costs and ensure support to the aggregate demand. The strategy followed was "the recession playbook" which was promoted in response to the GFC. This, consists in a combination of immediate rates cut at the effective lower bound and a consistent forward guidance. Hence, rates globally approached quickly zero or negative territory and central banks with policy rates above the lower bound, such as the Federal Reserve, the BoC, the BoE, the Reserve Bank of Australia and the Reserve Bank of New Zealand rapidly slashed their rates. Also emerging markets cut their policy rates aggressively, reaching the historical minimum in several countries. For instance, the largest interest rate reduction was operated in Turkey, where the central bank cut rates by 300 basis points (BPs). The central banks of Brazil, Mexico, Peru and South Africa reduced rates by more than 200 BPs, while those of Chile, Colombia, the Czech Republic, Hong Kong, Israel, India, the Philippines, Poland, Russia, Singapore, United Arab Emirates and Vietnam by more than 100 BPs. As discussed, interest rate policies adopted during the COVID-19 crisis in EMEs have been different from the previous ones. While in the past emerging economies were put under high pressure by the rapid appreciation of the dollar and the consequent outflow of capital and domestic currency depreciation, this time EME central banks were able to focus on the support of aggregate demand as key objective in their policy decisions. Two factors contributed: the first is the cyclical position of EMEs in the business cycle, giving more room for the easing of monetary policy; second, the prompt response of the FED and other AEs central banks improved global financial conditions, preventing a strong appreciation of the US dollar, generally considered a safe haven during period of economic downturns. Many central banks added forward guidance to interest rate cuts to compensate for the lower space available to reduce rates. The forward guidance strategy reflected at first the uncertainty of the crisis, leaving general indication except for few cases where implicit or explicit calendar guidance were used. EMEs central banks were more cautious in the use of forward guidance in part because most were still above the effective lower bound. Some of them, such as Brazil, used instead explicit forward guidance as an alternative to cutting rates lower.

Another type of policy that was deployed both in advanced and emerging markets economies were asset purchases programmes. Depending on specific countries' needs, they were of different designs. A common feature across all regions was that asset purchase programmes mainly involved long-term instruments. Central banks where the programmes were already effective mainly expanded their size, frequency and type of asset purchased. At the beginning, many central banks opted for buying government bonds, which accounted for half of total asset purchased, to contrast credit market dislocations and provide support to heightened credit risks. The ECB initially was more reluctant to intervene in the bond market, with the ECB's president Christine Lagarde, affirming that the ECB was not there "to close spreads". When the market reacted strongly to this announcement, the ECB governing council quickly shifted policy launching the 750 billions euro Pandemic Emergency Purchase Programme (PEPP), with the clear objective to expand monetary policy flexibility and provide stimulus to a larger extent of jurisdictions. The programme was then renewed twice in June and December to account for 1,850 billion euro. In addition to government bonds, some central banks extended their purchasing to public agency assets, provincial and municipal bonds. The FED and the Bank of Japan announced unlimited purchases of government bonds, while the Bank of Canada developed its first asset purchase programme. Also, EMEs started asset purchasing programmes, many for the first time. Therefore, their scope was much narrower. Central banks in Asia, Eastern Europe and Africa purchased government securities in the secondary market to restore liquidity and strengthening the monetary policy transmission mechanism to support aggregate demand, while Bank of Indonesia directly operated in the primary market. Latin America central banks, opted for a more cautious strategy since in the past, direct government financing had caused period uncontrolled hyperinflation. Only Colombia purchased a low level of public debt in the secondary market. Brazilian and Chilean central banks requested legal amendments from their respective legislative branches to enable them to purchase public bonds even if neither central bank used this policy during the crisis. The other half of the total asset purchasing programmes was directed to the private sector. In advanced economies, many central banks proposed tools built to directly support non-financial corporations. Regarding the characteristics, most programmes concerned the purchase of either commercial paper or corporate bonds, while a less extent included covered bond, equities and asset-backed or mortgage-backed securities with the ECB even extending eligibility to non-financial commercial paper. The Federal Reserve programme was mainly directed towards investment grade bonds. Later on the FED extended eligibility to subsequently downgraded bonds – the so-called "fallen angels" – either directly or through exchange-traded funds (ETFs). The ECB likewise extended eligibility to downgraded bonds against appropriate haircuts. The Bank of Japan quadrupled its purchases of commercial paper and corporate bonds, while the Bank of England announced that at least 10% of the 200 billions of additional purchases under its Asset Purchase Facility (APF) would involve corporate bonds. Looking at central banks in emerging markets, the Bank of Thailand provided funds to firms by purchasing investment-grade bonds maturing in 2020-21 to stabilise the corporate bond markets. Central banks of Chile and Colombia adopted private sector asset purchase programmes even if these were restricted to commercial bank bonds. Other countries, however, relied less on large and/or fast asset purchase programmes. These included several advanced economies such as Korea, Norway and Israel, which carried out some asset purchases but on a much smaller scale relative to GDP than during the GFC.

The financial markets turmoil that emerged immediately after the first COVID-19 outbreak forced central banks to provide liquidity to banks and support the availability of credit to the economy. Globally, around 60% of these programmes were newly established lending operations and more than half of them had a short-term maturity (one year or less). Regarding existing programmes, the lending operations entailed a larger size and wider eligibility conditions. In fact, in many cases, this involved an expansion in the type of entities eligible for support, including non-

Figure 3.4: Asset purchases by type of asset: regional and type division



Visual representation of asset purchase programmes during COVID-19 crisis by type of asset.
Source: BIS Working Papers "A global database on central banks' monetary responses to Covid-19"

bank lenders and broker-dealers. One main difference between existing and new lending policies was that many central banks introduced lending facilities directed to a range of private sector companies, including non-financial ones. A large extent of these programmes was intended to allow viable companies to overcome the period of economic limitation that characterized the first phases of the crisis. In general, to provide the flow of credit to households and corporations, central banks in AEs issued long-term lending measures bound to specific conditions. For example, The Federal Reserve, the Bank of Japan and the Bank of England established targeted lending programmes directed to banks at favourable conditions, conditional on the extension to medium-sized firms. In addition, to reach a larger spectre of SMEs, the Federal Reserve deployed the Main Street Lending Program, which provided four-years loans to firms that were in good financial standing before the crisis. To achieve the same goal of reaching companies with low access to financing instruments, many central banks put into place programmes under which low-cost funding was provided to lenders that increased their credit to the private sector. Some examples of these facilities are the Term Funding Scheme with additional incentives for SMEs (TFSME) in the UK, the Term Funding Facility (TFF) in Australia, the Fondo de Garantía para Pequeños Empresarios (FOGAPE) in Chile and various Support Facilities in China. But lending programmes directed to SMEs were also common in other countries like Thailand and Singapore. In many countries, especially in the EU, governments combined these lending schemes with programmes of loan guarantees. It is interesting to notice that some of these lending facilities were outside traditional central bank mandates. For example, the ECB's pandemic emergency longer-term refinancing operations (PELTRO) programme, which offered term loans to euro area banks at a rate below the ECB's deposit rate or the PBOC which provided special lending to facilitate issuing loans for 7,597 enterprises "which supported production and transportation of medical supplies and basic supplies".

Finally, there are a number of decisions supervisors in many countries have taken to support the provisions of credit. These decisions were generally meant to ease regulatory and macroprudential standards in the wake of the crisis to avoid negative effects of other policies on the flow of credit to households and businesses. The regulatory easing was directed to two main areas. The first aimed to soften regulatory capital, like reducing counter-cyclical or systemic risk capital buffers and liquidity requirements. Often these measures were combined with strict restrictions on dividend distributions. The second focused on allowing regulatory forbearance on assets and loan valuations, such as easing collateral eligibility rules and allowing banks to apply more favourable valuations of assets and lower risk weights for certain loans, as well as providing more flexibility in the treatment of non-performing loans. Quite often these measures included policies encouraging banks to help borrowers affected by the pandemic to restructure loans and grant moratoria on loan repayments to SMEs and individuals.

Despite the pandemic is still far from over, it is possible to draw the first conclusions on the role central banks' response had in limiting adverse effects. Central banks have effectively responded to the initial phases of the COVID shock thanks to a combination of powerful monetary policies built in the wake of the GFC, and of an entirely new set of tools that directly supported financial markets and provided the flow of credit to the economy. Importantly, this response has required an unparalleled expansion of reach, well beyond the narrow inflation-targeting focus of most central banks. These programmes were crucial to stabilise economies and financial markets when production was blocked and while vaccines were developed and rolled out. However, this expansion of reach and responsibilities also raises numerous questions about potential negative effects and the role of central banks in the future.

3.2 COVID-19 short and long-term effects on firms

The social and economic restrictions caused by the COVID-19 pandemic have strongly impacted corporate profitability and leverage all over the world. Revenues and profits fell by 2 percentages points for the median firm, debt and consequently leverage raised and the interest coverage ratio (a key measure to identify zombie firms), declined by 2%[6]. The large decline in revenue for many companies has been caused by the sudden supply shock that impaired previous methods of economic production, from goods to services. In addition to this, uncertainty raised by the virus and the associated restrictions changed consumption patterns, creating substantial losses and urgent liquidity injections to ensure businesses' financial viability. However, this grim picture conceals wide heterogeneity, depending on the sector, of the impact the pandemic had on firms. Many industries, in particular those with high fixed costs, faced liquidity needs and cash flow pressures caused by the drop in sales and changes in consumer behaviours. Among the hardest hit industries, firms in the energy sector saw their revenues and profits plunge between 30% and 50% due to depressed oil prices determined by the lockdown measures. Also, sectors linked to tourism like airlines, travel and leisure have all been strongly impacted by the COVID-19 outbreak, so as the contact-intensive consumer services, such as hotel and restaurant chains, casinos and gaming, and cruise lines. The income shock was also sizeable in the transportation and automobile sectors.

[6]For further details see Puy and Rawdanowicz (2021) "COVID-19 and the corporate sector: Where we stand"

In contrast, firms operating in software services, pharmaceuticals, healthcare or retailing expanded their turnover substantially in fiscal year 2020, both in terms of revenues and profits. The sudden stop of the production activities of many companies and the change in consumption patterns has put into jeopardy an enormous amount of jobs, raising the unemployment rate in almost every country. Self-employed and micro enterprises have suffered the most the immediate effect of the pandemic since they are often less resilient to shocks than larger firms. In fact, these class of companies have typically fewer routes to access private capital and have greater dependency on fewer suppliers. Another short-term effect of the COVID-19 pandemic crisis has been the disruption of supply chains due to its global and massive nature. In particular, the initial outbreak in China produced plants closures and supply shortages that affected global supply chains even before the virus reached other parts of the world. It is sufficient to notice that, 938 of the Fortune 1000 corporations have tier 2 suppliers in the Chinese provinces most affected by the virus. Moreover, when China finally began to lift its lockdowns, other economies were implementing their own. All these mechanisms, combined with the risk of further disruption to consumer demand and business' supply, may persistently shift the profitability of several industries and accelerate trends already in place. As a result, they can have a direct role in increasing the number of zombie firms.

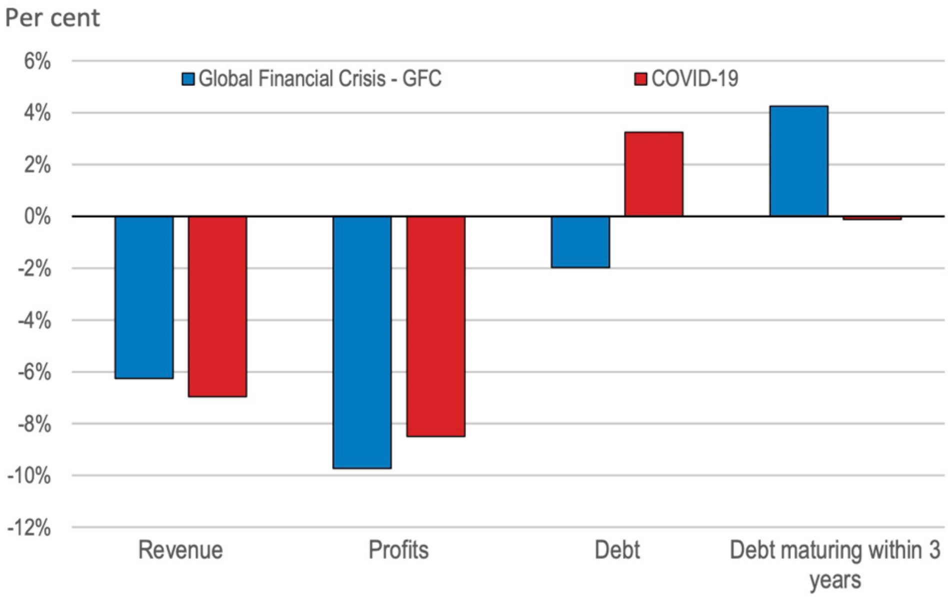
Even if the shock caused by the crisis has been very heterogeneous across sectors, the speed and the scale of its impact on the economy has prompted extraordinary financial support to firms by governments and central banks. Therefore, in the initial phase the overarching goal was to avoid the most immediate and extreme consequences of the crisis. In particular, governments and central banks deployed trillions of dollars to limit the corporate liquidity crisis. This support has taken the form of public credit guarantee schemes, debt moratoria, direct support to firms via financial aid programmes, central bank lending and purchase programmes and a loosening of micro and macro-prudential supervisory rules[7]. In this way, the immediate and most alarming short-term effects of the crisis have been averted by a prompt response of policymakers. Furthermore, as already seen in the previous section, financial markets disruption has been largely contained due to immediate and effective monetary and fiscal policy support. However, while these measures were necessary to prevent a wave of layoffs and defaults, it has inflated the debate on whether such policies are able to promote zombie lending and zombie firms. In fact, it is reasonable to expect that financial support from governments and central banks may influence the scope for zombie lending. Government support schemes are extremely important to provide relief to viable firms in liquidity need, allowing them to obtain the resources to survive. However, they can also impair the Schumpeterian creative destruction mechanisms and generate moral hazard when there is no selecting mechanism in place to ensure that only companies that are actually in need receive support. At the same time, the provision of central bank liquidity facilities and low interest rates policy has a role in funding illiquid but viable firms. However, they may also affect zombie lending by allowing indebted firms to refinance their debt at lower interest rates, preventing in this way the orderly restructuring of non-viable firms[8].

[7]See, for example, Gourinchas et al. (2020) for a detailed overview of the fast-expanding academic research on the effectiveness of the initial policy response to the COVID economic crisis

[8]See: Acharya et al. 2020

Despite the range of firms affected by the consequences of the COVID-19 shock, the number of companies in 'in distress' – measured by the share of firms with either negative equity or an interest coverage ratio below one – has remained stable[9]. As observed also by the OECD[10], the number of bankruptcies among both large and SMEs in these countries has diminished. In fact, the number of bankruptcies remained lower than in the GFC, and in some AE it was even lower than in the years preceding the pandemic. The most likely explanation for this counterintuitive outcome is that governments and central banks have provided the sufficient financial and liquidity support for the firms most at risk. However, the favourable reduction in the number of bankruptcies due to generous liquidity measures has come at the expenses of an increase in corporate debt, especially in those sectors that are most affected by the pandemic. About this topic, in *figure 3.5*, it is possible to look at the comparison between how risky firms faced the COVID-19 pandemic and the GFC. During the financial crisis of 2008, less solid firms in hard hit sectors experienced both a reduction in their access to credit and a steep shortening of their debt maturity structure. During COVID-19, the same firms managed to raise a significant amount of debt, without incurring any change in debt maturity, even though they faced a revenue shock of similar magnitude.

Figure 3.5: The COVID-19 crisis and the Global Financial crisis different effects on risky firms



Firms are defined as "risky" if their ICR in 2019 was in the bottom tercile of their respective industry and if they belong to a hard-hit sector. A hard-hit sector is defined as an industry that lost, on average, more than the median industry.
Source: VOX EU CEPR, "Covid-19 and the corporate sector: Where we stand"

A major difference between the two crises is the solidity of the banking system. In the COVID-19 crisis, while corporate bond markets and money market funds were put under great pressure, the banking sector has shown considerable resilience. This partly reflects the stronger financial position in which banks found themselves following the large reforms in the aftermath of the GFC, when the banking sector was recapitalized and subject to more prudent regulation and supervision.

[9]In the fiscal year 2020, 5% of firms reported negative equity, and less than 2% an ICR below one. These numbers are almost unchanged compared to FY 2019

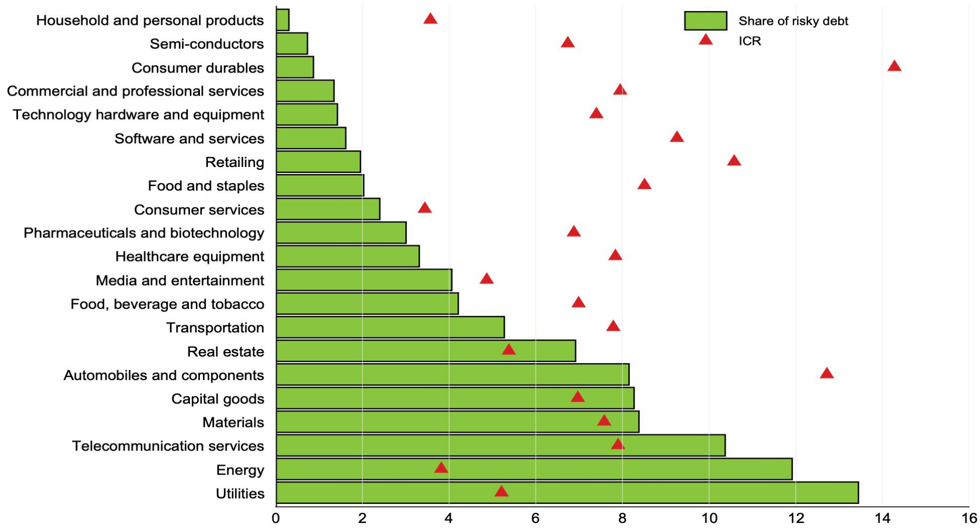
[10]See: Djankov and Zhang 2021

In addition, most economies have reached the coronavirus crisis with a better risk management and flexible stress testing tools that allowed for a timely insight into banks' risk exposure. Differently from 2008, the Coronavirus crisis has impacted first on the balance sheets of firms in the real economy, with the potential risk of spreading to the balance sheets of banks. According to the Institute of International Finance, global levels of debt in the non-financial corporate sector have risen from 73% at the beginning of 2007 to 91% at the beginning of 2020, and in emerging markets alone, levels increased from 62 percent to 91 percent of GDP between 2007 and 2020. Lower interest rates have also allowed fragile companies to accumulate more debt, increasing however, the risks that these unprofitable firms become zombie. Another challenge that raises concern in the medium-long term is the growing lower quality of corporate credit. Among the non-financial corporate debt stock currently rated by S&P, around 30% consists of entities rated as "speculative", namely companies that face difficulty in repaying debt. At the same time, 40% of the overall rated firms are entities with only a BBB rating, which is the lowest rating in the investment grade category. Luckily, the COVID-19 shock has had a limited impact on the sectors that have issued most of the risky debt at the global level, such as utilities and telecommunications (see *figure 3.6*). The consumer services sector, which has been hit the hardest, reported the lowest median interest coverage ratio in fiscal year 2020 among all industries. This accounts for only a small portion of the lower quality debt stock. Still, solvency challenges remain in several industries, especially where the corporate debt is due to mature in 2024, at a time when it is possible that policy interest rates will be higher than when some of the debt was issued. The higher level of corporate debts in many countries implies that a large number of firms entered this crisis in condition of financial stress. Therefore, there are concerns that the ample financial support deployed by policymakers all over the world may create a wave of zombies due to the conditions in which the non-financial corporate sector was already in.

3.3 How to prevent zombification

Although the COVID-19 pandemic has demanded unprecedented credit support to firms, intensifying the debate around the peril of a rise in zombie firms, there are several reasons to believe that this effect can be averted in the long term. First, the pandemic has hit the most those industries that were in solid financial shape. The exogeneity and temporary nature of the shock make possible for these sectors to recover once the economic activity bounces back. Therefore, the profitability gap will only be limited. Furthermore, the fact that banks entered the economic downturn with better capitalisation relative to the GFC reduces the incentive for zombie lending and loans "evergreening". Finally, the large-scale economic support of governments and central banks has avoided the liquidity crisis to turn into a solvency crisis and the usual crowding-out effect of zombie lending is less powerful when the business environment is supported by large liquidity provisions and depressed credit demand. The nature of the shock involves that firms that normally would be classified as zombie are in reality viable firms, with temporary liquidity issues since the virus containment measures have led to a collapse in aggregate demand. The real chal-

Figure 3.6: Risky debt and the median interest coverage ratio by industry



Risky debt refers to the total amount of debt (both loans and bonds) in firms rated BBB or speculative, as of fiscal year 2019. The median ICR reports the median fiscal year 2020 ICR of firms with a BBB or speculative rating operating in each industry, using 2020 firms' debt size as weights.
Source: VOX EU CEPR, "Covid-19 and the corporate sector: Where we stand"

lenge in this emergency environment, is to ensure that funds are directed toward firms that have been affected by the pandemic. However, there is no efficient sorting mechanisms that can be put in place to secure funding to illiquid firms only and not to insolvent ones. In such a crisis it is extremely hard and time consuming to distinguish illiquid from insolvent firms. Government intervention therefore, faces a trade-off between keeping the economy afloat and the risk of funding some insolvent firms[11]. Of course, the longer the pandemic lasts, the more damage will be done to the real economy, reducing cash buffers and pushing firms over the cliff into bankruptcy. The risk that zombification arises then grows as time passes.

Hence, the crucial matter is to select the best measures to prevent zombification. Recent researches suggest that four policy areas are able to reduce the scope of zombie lending. First, it is necessary to fine-tune the credit guarantees and subsidies governments and central banks have put in place quickly during the outbreak of the pandemic. At the same time, it is important to understand when is the right moment to exit from these credit guarantee schemes. Gobbi et al. (2020) argue that the introduction of credit guarantees increases the collateral value of a loan above its non-guaranteed value, encouraging bank lending. By the same reasoning, the closure of guarantee schemes will inversely reduce collateral values, potentially boosting loan foreclosures. Another mechanism that would produce a smooth phasing out of government credit guarantees is the adoption of equity financing schemes instead of debt. The promotion of measures that introduce equity instruments to finance firms instead of debt-based instruments would largely avoid the cliff effects on bank lending and at the same time reduce the incentive for zombie lending. Second, since it has been widely studied that weakly-capitalised banks tend to incur in zombie lending more than solid

[11]See: Gourinchas et al. 2020, Gagnon 2020

banks, it is important to promote sound capital positions for banks. In this sense, the role of supervisory authorities and the reforms put into place to build a resilient banking system are necessary to ensure the proper functioning of the lending channel. Recent supervisory recommendations for banks to temporarily scrap dividends and share repurchases go in the correct direction of maintaining solid capital levels. Third, banks are required to set up efficient risk management procedures and adequate provision mechanisms. As the pandemic evolves and it becomes clearer which borrowers are viable or not, supervisory authorities need to ensure that banks plan adequately for loan losses on a forward-looking basis. Recognising and provisioning for loan losses reduces zombie lending as it removes the incentive to hold on to these loans (Bonfim et al. 2020). Moreover, this would promptly tackle the build-up of non-performing loans in case of rising corporate defaults leaving banks in a safer position. Finally, and from a longer-term perspective, it is of great importance to improve the efficiency of insolvency frameworks and bankruptcy laws, as the evergreen incentive is stronger in environments with weak insolvency mechanisms. Within Europe, this calls for further efforts to harmonise insolvency frameworks across countries, as foreseen under the Capital Markets Union action plan.

Conclusion

This thesis focused on the relationship between monetary policies and zombie firms, both from a theoretical and empirical perspective. In particular, the analysis covered the main themes of discussion in the economic literature, the empirical evidences of monetary policies' influence on zombie companies and the risk of a new wave of corporate zombification in the wake of the COVID-19 crisis.

The first chapter presented an overview of the topic of zombie firm. As discussed, these companies have a different financial structure and investment behaviour than profitable firms and show lower levels of employment and productivity growth. In addition, researchers have detected a persistent increase in their share in the last decades, a tendency to increment in coincidence with economic recessions and a rising propensity to remain zombie over time. Still, a number of open questions remain due to the dispute over the proper identification strategy to use. Notably, the issue over their size is an important element to better understand zombies' distribution. The main causes and consequences of zombie firms were also examined in detail. Researches concentrate on two factors that may create the conditions for their proliferation: forbearance lending and monetary policy. The first relates to a situation in which banks with structural weaknesses have the incentive to adopt risky actions that lead to the practice of "zombie lending". The second cause is linked with the benefit a fall in interest rates and liquidity provisions to banks bring to indebted firms. This relation has only been partially studied by the economic literature. Still, striking causality links have been found. As an example, Banerjee and Hofmann (2018) show that the decrease of nominal interest rates is able to raise the share of zombie firms in sectors strongly dependent on external funding. At the same time, a large part of the literature has discussed the impact zombie firms have on healthier peers. The mainstream position is that zombies may create the so-called "congestion effect". In practice, they are able to crowd out growth of more profitable firms by locking resources and depressing prices and profits in their sector. Several empirical analyses have shown a significant relationship between the increase in the share of zombie enterprises and the fall in investments and employment in more productive companies. However, an innovative and opposite argument discussed by Schivardi, Sette and Tabellini (2020) can change the way economic literature assesses zombie companies' effects on their peers. In their two companion papers, the authors explain the "identification problem" of the traditional literature on zombie firms. According to their articles, previous researches failed to identify a bias that led to observe the presence of negative spillovers even when this was not the case. As a consequence, their claim is that under general conditions on firms' performance distribution, there is no causal meaning between the increase in the share of zombie enterprises and the worsening of healthier companies' performance.

The idea that expansionary monetary policy has the ability to increase the number of zombie firms has been supported by a substantial segment of the economic literature. Nevertheless, researches have only been partial and limited to specific monetary tools[12]. In this regard, it relates the innovative contribution of this study to the existing literature. In fact, the empirical part of the thesis aimed to provide a model explaining the general process that allows monetary policy to affect zombie lending. The underlying reasoning is based on the idea that, when central banks actively support the economy by setting lower interest rates and providing liquidity, they contribute to establish relaxed credit conditions. These may reduce pressure on debtors to improve their balance sheets and on creditors to recover expected losses. In addition, liquidity injections alter banks' credit supply and risk aversion, leading to riskier decisions. The model described this link through the analysis of two channels: the bank lending channel and the corporate lending channel. Hence, the empirical analysis presented a blueprint to measure the influence of credit supply, in the presence of expansionary monetary policies, on the likelihood of zombie firms to obtain credit. In particular, the money supply directed to banks was used as instrument and the corporate loan volume of banks as endogenous variable. The analysis, showed a statistically significant positive effect of the fitted value of credit supply on the likelihood of a zombie firm to obtain credit. Looking at the margins analysis it was possible to isolate this effect. In particular, when the amount of aggregate loans (weighted by the assets owned by the bank) increases by a very small amount, the likelihood of a zombie firm to obtain credit raises by 1.39%. Therefore, expansionary monetary policies contribute to create the conditions for the rise in zombie firms, which in turn determine resources' misallocation and lower aggregate productivity. Should this effect be strong enough, it could even have distorting effect on the economy and monetary policies themselves. These results suggest that, when stimulating aggregate demand and investment with expansionary monetary policies, central banks should also consider the impact these measures have on zombie firms.

The final chapter was dedicated to the analysis of the COVID-19 economic crisis and its effects on zombie firms. The virus has quickly spread across the world evolving into a health pandemic and causing severe disruptions to economic activities. The COVID-19 pandemic crisis has been an economic shock of unprecedented magnitude and its consequences have been felt worldwide, impacting almost any country and simultaneously affecting demand, supply and financial conditions. At the beginning, the corporate bond market was the epicentre of the financial turmoil but then, also the sovereign debt market, the stock market and the money market were severely affected. Central banks reacted strongly to avoid a new financial crisis, deploying measures on several fronts. Policymakers used the experience of the precedent crisis, reinforcing previous tools and adopting new strategies and specific instruments to enlarge the scope of their actions. At the same time, the social and economic restrictions imposed to curb the virus have strongly impacted the corporate sector. Firms have suffered from a fall in profitability, higher leverage and disruptions of supply chains. However, the real long-term effects on the corporate environment are still unclear. These factors represent renewed concerns for a future possible rise in the share of zombie firms, as happened

[12] See: Banerjee and Hofmann (2018) and Acharya et al. (2019)

after the GFC. Still, there are reasons to expect that this time can be different. Therefore, policies directed to prevent a rise in zombification and direct the recovery toward a more viable condition are extremely important.

The goal of this work was to provide a general framework for the study of the relationship between monetary policy and zombie companies and present the outstanding issues in the literature. In this contest of high uncertainty, where monetary policy was pivotal in preventing the direst consequences of the crisis and in supporting the recovery of the economic activity, the comprehension of its side effects is more important than ever. Therefore, more thorough analyses, which fell outside the scope of this thesis, are required in the near future to develop better policies that limit the harmful effects of zombie firms.

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Appendix

This brief appendix is provided to show the codes used to manipulate the data, create the final data set, carry out the implementation of the model and further data analyses.

A.1 MATLAB codes

The first set is relative to the work done on MATLAB to transform the raw data downloaded into group of ordered data set. The first figure shown describes the codes used to identify the zombie firms among all the firms' data downloaded. To do so, those with an interest coverage ratio (ICR) less than one for at least three consecutive years were highlighted.

Zombie Firms' Selection Codes

```
clc;
clear;
opts = detectImportOptions('Firms_Data.xlsx'); %Excel file of data on all firms
preview('Firms_Data.xlsx',opts);
opts.Sheet = 'Zombie_Firms'; %Recall excel sheet
opts.SelectedVariableNames = [1:30];
opts.DataRange = 'A2:AE1036';
T = readtable('Firms_Data.xlsx',opts); %Download data
```

```
X = T(:,2:end); %Full matrix of data
X = table2array(X); %Convert it into an array
N = size(X,1); %Number of firms
K = 10;
```

```
IC = zeros(N,K); %For loop to create a vector of Interest Cover Ratio for each firms
for j=1:N;
    IC(1:N,1:end)= X(:,1:10)./X(:,11:20);
end;
```

```
Names = T(:,1); %Vector of names of the firms
Names = cellstr(reshape([Names{:,:}],size(Names)));
Names = string(Names); %Convert them into strings
```

```
IC = IC<= 1; %Highlights those with an ICR less than one
Choose = table(Names, IC(:,1), IC(:,2), IC(:,3), IC(:,4), IC(:,5), IC(:,6), ...
    IC(:,7), IC(:,8), IC(:,9), IC(:,10));
Choose.Sum = sum(Choose{:,2:end},2); % select those with at least three ICR < than 1
```

Then, the objective was to build a panel data set covering all the variables and data needed to carry out the econometric analysis. Therefore a process of manipulation was carried out in order to organize the data. Each set of codes below is meant to create a column vector that composes a part of the final panel data.

Create the Panel Data Set

```
clc;
clear;
```

Create a column vector that repeats years from 2011 to 2020 for each firm

```
opts1 = detectImportOptions('Main_File.xlsx'); %Recall excel file of raw data
preview('Main_File.xlsx',opts1);
opts1.Sheet = 'Money_Supply'; %Recall sheet of raw data
Years = readtable('Main_File.xlsx',opts1);
Years = Years(:,1);
Years = table2array(Years);
Years = repmat(Years,66,1);
```

Create the column vector of credit obtained by zombie firms

```
opts1 = detectImportOptions('Main_File.xlsx'); %Recall excel file of raw data
preview('Main_File.xlsx',opts1);
opts1.Sheet = 'ZF_Credit'; %Recall sheet of raw data
ZFCredit = readtable('Main_File.xlsx',opts1);
ZF_Credit = ZFCredit(:,2:(end-2)); %Select data of interest only
ZF_Credit = table2array(ZF_Credit); %Convert into an array
ZF_Credit = ZF_Credit';
ZF_Credit = reshape(ZF_Credit,1,[])'; %Convert it into a column vector
```

Same process for the names of zombie firms

```
ZFName = ZFCredit(:,1); %Select the names only
ZFName = table2array(ZFName); %Convert into an array
ZFName = repelem(ZFName,10); %Repeat each 10 times maintaning the order
```

Banks' corporate loans weighted by their assets

```
opts = detectImportOptions('Main_File.xlsx');
preview('Main_File.xlsx',opts);
opts.Sheet = 'ZFBANK_REL';
WBanksLoans = readtable('Main_File.xlsx',opts);
WBanksLoansValues = WBanksLoans(:,2:(end-2));
WBanksLoansValues = table2array(WBanksLoansValues);
WBanksLoansValues = WBanksLoansValues';
WBanksLoansValues = reshape(WBanksLoansValues,1,[])';
```

Name of banks acting as main arrangers

```
WBanksLoansName = WBanksLoans(:,1);
BanksName = table2array(WBanksLoansName);
BanksName = repelem(BanksName,10);
```

Aggregate money supply toward banks

```
opts = detectImportOptions('Main_File.xlsx');
preview('Main_File.xlsx',opts);
opts.Sheet = 'Money_Supply';
MoneySupply = readtable('Main_File.xlsx',opts);
MoneySupply = MoneySupply(:,2);
MoneySupply = table2array(MoneySupply);
MoneySupply = repmat(MoneySupply,66,1);
```

Zombie firms' total assets

```
opts = detectImportOptions('Main_File.xlsx');
preview('Main_File.xlsx',opts);
opts.Sheet = 'ZF_Assets';
TA = readtable('Main_File.xlsx',opts);
TA = TA(:,2:(end-2));
TA = table2array(TA);
TA = TA';
TA = reshape(TA,1,[])';
```

Countries' aggregate syndicated loans

```
opts = detectImportOptions('Main_File.xlsx');
preview('Main_File.xlsx',opts);
opts.Sheet = 'SyndLoans';
TL = readtable('Main_File.xlsx',opts);
TL = TL(:,2:(end-2));
TL = table2array(TL);
TL = TL';
TL = reshape(TL,1,[])';
```

Finally, this section shows the correlation analysis carried out to compare the aggregate corporate loans volume of the data set with the actual syndicated loans volume in the euro zone.

Measure correlation between data aggregate corporate loans and euro zone syndicated loans

```
clc
clear
```

Codes

```
Comparison = readtable('BankComparison.xlsx'); %Recall excel data
Data = table2array(Comparison); %Convert them into an array
EZ = Data(:,3); %Select data on eurozone syndicated loans
BanksLoans = Data(:,2); %Select data on data set banks' loans
Corr = corr(BanksLoans,EZ) %Measure their correlation
```

```
Corr = 0.8353
```

A.2 Panel data tables

Panel Data

Year	ZF	credit	BanksName	w_bankloans	MoneySupply	log_moneysupply	ZF_TotalAsset	log_zftotasset	CountrySyndLoans	log_countrysyndloans
2011	OUTOKUMPUOYJ	1	Nordea	0.25846953	1277450000	20.96813174	5227000	15.46934806	6230	8.737131612
2012	OUTOKUMPUOYJ	1	Nordea	0.27354088	1390483000	21.05291701	9671000	16.08464227	6514	8.781708986
2013	OUTOKUMPUOYJ	1	Nordea	0.29374843	776770000	20.47065485	8823000	15.99287251	6940	8.845057054
2014	OUTOKUMPUOYJ	0	Nordea	0.21782138	636011000	20.27072642	6411000	15.67352582	6234	8.73777346
2015	OUTOKUMPUOYJ	0	Nordea	0.22457132	771404000	20.46372279	5874000	15.58604639	6648	8.802071337
2016	OUTOKUMPUOYJ	0	Nordea	0.21730861	1020081000	20.74314787	5990000	15.60560197	7144	8.874028123
2017	OUTOKUMPUOYJ	0	Nordea	0.22796297	1460111000	21.1017783	5887000	15.58825709	6593	8.793763759
2018	OUTOKUMPUOYJ	0	Nordea	0.24150538	1347023000	21.02116281	5998000	15.60693664	7547	8.928905412
2019	OUTOKUMPUOYJ	1	Nordea	0.26722454	851611000	20.56264041	6038000	15.61358339	7983	8.98506956
2020	OUTOKUMPUOYJ	0	Nordea	0.25168973	2477057000	21.630337	5797000	15.5728511	9688	9.178643285
2011	SARASS.P.A.	1	INTESASANPAOLO	0.01835046	1277450000	20.96813174	4152757	15.23928301	131207	11.78453151
2012	SARASS.P.A.	1	INTESASANPAOLO	0.01859165	1390483000	21.05291701	3939922	15.18667148	124349	11.73084741
2013	SARASS.P.A.	0	INTESASANPAOLO	0.01859543	776770000	20.47065485	3813531	15.15406609	104534	11.55726766
2014	SARASS.P.A.	0	INTESASANPAOLO	0.01762457	636011000	20.27072642	3862008	15.16669781	93057	11.44096749
2015	SARASS.P.A.	1	INTESASANPAOLO	0.01727723	771404000	20.46372279	3317576	15.01474495	90070	11.40834242
2016	SARASS.P.A.	0	INTESASANPAOLO	0.014862	1020081000	20.74314787	2894384	14.87828287	97105	11.48354815
2017	SARASS.P.A.	0	INTESASANPAOLO	0.01410158	1460111000	21.1017783	3157161	14.96518376	92578	11.43580681
2018	SARASS.P.A.	0	INTESASANPAOLO	0.0142081	1347023000	21.02116281	2959919	14.90067246	101800	11.53076538
2019	SARASS.P.A.	0	INTESASANPAOLO	0.01255725	851611000	20.56264041	3563984	15.08638958	101838	11.53113859
2020	SARASS.P.A.	1	INTESASANPAOLO	0.01152886	2477057000	21.630337	3370188	15.03047909	122385	11.71492709
2011	BILFINGERSE	1	HSBCCONTINENTALEUROPE	0.19914179	1277450000	20.96813174	7719600	15.85927311	160605	11.98670321
2012	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.17113957	1390483000	21.05291701	6849900	15.73974461	153277	11.94000202
2013	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.11032442	776770000	20.47065485	6531500	15.69214718	143751	11.87583792
2014	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.11794466	636011000	20.27072642	5961600	15.60084946	143291	11.87263281
2015	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.14002897	771404000	20.46372279	5184500	15.46118396	149323	11.91386702
2016	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.14597782	1020081000	20.74314787	4018900	15.20651879	155024	11.95133522
2017	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.16373012	1460111000	21.1017783	3620300	15.10206745	160125	11.98371004
2018	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.14919921	1347023000	21.02116281	3476000	15.06139277	187192	12.13989011
2019	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.14845591	851611000	20.56264041	3354800	15.02590271	207035	12.24064314
2020	BILFINGERSE	0	HSBCCONTINENTALEUROPE	0.14407484	2477057000	21.630337	3256300	14.99610214	214756	12.27725778
2011	VALLOUREC	1	BNPPARIBAS	0.14717988	1277450000	20.96813174	9194809	16.03414964	122515	11.71598875
2012	VALLOUREC	0	BNPPARIBAS	0.05735219	1390483000	21.05291701	9241105	16.03917203	109800	11.60641581
2013	VALLOUREC	0	BNPPARIBAS	0.05002956	776770000	20.47065485	9300187	16.04554507	99335	11.50625326
2014	VALLOUREC	0	BNPPARIBAS	0.04196364	636011000	20.27072642	9231555	16.03813806	107866	11.588645
2015	VALLOUREC	0	BNPPARIBAS	0.04329418	771404000	20.46372279	6991284	15.76017479	111442	11.62125956
2016	VALLOUREC	0	BNPPARIBAS	0.044782	1020081000	20.74314787	8132351	15.91136062	123601	11.72481391
2017	VALLOUREC	0	BNPPARIBAS	0.0450166	1460111000	21.1017783	6886383	15.74505654	135902	11.81968932
2018	VALLOUREC	0	BNPPARIBAS	0.04780756	1347023000	21.02116281	6413045	15.67384476	155534	11.95461964
2019	VALLOUREC	0	BNPPARIBAS	0.04928758	851611000	20.56264041	7305436	15.80412929	173270	12.06260635
2020	VALLOUREC	0	BNPPARIBAS	0.04717422	2477057000	21.630337	5048288	15.43455973	200613	12.20913296
2011	HEIJMANSNV	0	ABNAMROBANKNV	0.21432916	1277450000	20.96813174	1553556	14.25605705	22256	10.01036691
2012	HEIJMANSNV	0	ABNAMROBANKNV	0.21858138	1390483000	21.05291701	1386224	14.14209406	24052	10.08797343
2013	HEIJMANSNV	0	ABNAMROBANKNV	0.33266563	776770000	20.47065485	1202809	14.00017021	23293	10.05590817
2014	HEIJMANSNV	0	ABNAMROBANKNV	0.32198246	636011000	20.27072642	1204690	14.00173283	23970	10.08455833
2015	HEIJMANSNV	0	ABNAMROBANKNV	0.33137653	771404000	20.46372279	1189963	13.98943277	23530	10.06603148
2016	HEIJMANSNV	0	ABNAMROBANKNV	0.29982463	1020081000	20.74314787	1056168	13.87015782	26259	10.17576407
2017	HEIJMANSNV	0	ABNAMROBANKNV	0.29748901	1460111000	21.1017783	770803	13.55518811	26191	10.17317112
2018	HEIJMANSNV	0	ABNAMROBANKNV	0.29053664	1347023000	21.02116281	776106	13.56204439	28887	10.27114695
2019	HEIJMANSNV	0	ABNAMROBANKNV	0.27954796	851611000	20.56264041	898395	13.70836512	30140	10.31360847
2020	HEIJMANSNV	0	ABNAMROBANKNV	0.23177106	2477057000	21.630337	930638	13.74362565	30997	10.3416457
2011	ADLERREALESTATEAG	1	DEUTSCHEBANKAG	0.01051429	1277450000	20.96813174	34709	10.4547543	160605	11.98670321
2012	ADLERREALESTATEAG	1	DEUTSCHEBANKAG	0.01147371	1390483000	21.05291701	43764	10.68656684	153277	11.94000202
2013	ADLERREALESTATEAG	1	DEUTSCHEBANKAG	0.0132841	776770000	20.47065485	460888	13.04091034	143751	11.87583792
2014	ADLERREALESTATEAG	1	DEUTSCHEBANKAG	0.01499324	636011000	20.27072642	1416459	14.16367065	143291	11.87263281
2015	ADLERREALESTATEAG	1	DEUTSCHEBANKAG	0.01656958	771404000	20.46372279	3076246	14.93922058	149323	11.91386702
2016	ADLERREALESTATEAG	0	DEUTSCHEBANKAG	0.01841506	1020081000	20.74314787	3430477	15.04820988	155024	11.95133522
2017	ADLERREALESTATEAG	0	DEUTSCHEBANKAG	0.01863254	1460111000	21.1017783	3778967	15.14496125	160125	11.98371004
2018	ADLERREALESTATEAG	1	DEUTSCHEBANKAG	0.153003	1347023000	21.02116281	5856631	15.58308508	187192	12.13989011
2019	ADLERREALESTATEAG	1	DEUTSCHEBANKAG	0.17560497	851611000	20.56264041	10681677	16.1840404	207035	12.24064314
2020	ADLERREALESTATEAG	0	DEUTSCHEBANKAG	0.16467272	2477057000	21.630337	6292313	15.65483929	214756	12.27725778
2011	GRUPOEMPRESARIALSANJOSES.A.	1	BANCOBILBAOVIZCAYAARGENTARIASA	0.02200479	1277450000	20.96813174	2897080	14.87921389	111780	11.62428793
2012	GRUPOEMPRESARIALSANJOSES.A.	1	BANCOBILBAOVIZCAYAARGENTARIASA	0.01774736	1390483000	21.05291701	2790846	14.84185533	136345	11.82294372
2013	GRUPOEMPRESARIALSANJOSES.A.	0	BANCOBILBAOVIZCAYAARGENTARIASA	0.0166691	776770000	20.47065485	2465245	14.71780175	101715	11.52993006
2014	GRUPOEMPRESARIALSANJOSES.A.	1	BANCOBILBAOVIZCAYAARGENTARIASA	0.01584797	636011000	20.27072642	2405248	14.69316357	111810	11.62455628
2015	GRUPOEMPRESARIALSANJOSES.A.	0	BANCOBILBAOVIZCAYAARGENTARIASA	0.01791014	771404000	20.46372279	984849	13.80024361	104503	11.55697106
2016	GRUPOEMPRESARIALSANJOSES.A.	0	BANCOBILBAOVIZCAYAARGENTARIASA	0.02032777	1020081000	20.74314787	1022619	13.83787754	101740	11.53017582
2017	GRUPOEMPRESARIALSANJOSES.A.	0	BANCOBILBAOVIZCAYAARGENTARIASA	0.03290298	1460111000	21.1017783	964376	13.77923654	93758	11.44847227
2018	GRUPOEMPRESARIALSANJOSES.A.	0	BANCOBILBAOVIZCAYAARGENTARIASA	0.02576664	1347023000	21.02116281	995797	13.8112987	92595	11.43599042
2019	GRUPOEMPRESARIALSANJOSES.A.	0	BANCOBILBAOVIZCAYAARGENTARIASA	0.02472627	851611000	20.56264041	1000272	13.81578252	89276	11.39948797
2020	GRUPOEMPRESARIALSANJOSES.A.	0	BANCOBILBAOVIZCAYAARGENTARIASA	0.02111452	2477057000	21.630337	988502	13.80394594	95055	11.46221095
2011	SRVYHTIOTOYJ	1	OPCORPORATEBANKPLC	0.29218317	1277450000	20.96813174	588348	13.28507389	6230	8.737131612
2012	SRVYHTIOTOYJ	0	OPCORPORATEBANKPLC	0.29363535	1390483000	21.05291701	675369	13.42301449	6514	8.781708986
2013	SRVYHTIOTOYJ	1	OPCORPORATEBANKPLC	0.29342348	776770000	20.47065485	662989	13.40451368	6940	8.845057054
2014	SRVYHTIOTOYJ	0	OPCORPORATEBANKPLC	0.2711427	636011000	20.27072642	576067	13.26397925	6234	8.73777346
2015	SRVYHTIOTOYJ	1	OPCORPORATEBANKPLC	0.25844713	771404000	20.46372279	762620	13.54451515	6648	8.802071337
2016	SRVYHTIOTOYJ	0	OPCORPORATEBANKPLC	0.0868354	1020081000	20.74314787	882486	13.6904982	7144	8.874028123
2017	SRVYHTIOTOYJ	1	OPCORPORATEBANKPLC	0.09030946	1460111000	21.1017783	888526	13.69731919	6593	8.793763759
2018	SRVYHTIOTOYJ	1	OPCORPORATEBANKPLC	0.09809859	1347023000	21.02116281	947033	13.76108922	7547	8.928905412

2019	SRVYHTIOTOYJ	1	OPCORPORATEBANKPLC	0.10534543	851611000	20.56264041	913334	13.72485692	7983	8.98506956
2020	SRVYHTIOTOYJ	0	OPCORPORATEBANKPLC	0.09316972	2477057000	21.630337	898918	13.7089471	9688	9.178643285
2011	SGLCARBONSE	1	LANDESBANKHESSEN-THUERINGENGIR	0.37997378	1277450000	20.96813174	2271300	14.63586291	160605	11.98670321
2012	SGLCARBONSE	0	LANDESBANKHESSEN-THUERINGENGIR	0.32714337	1390483000	21.05291701	2559700	14.75540062	153277	11.94000202
2013	SGLCARBONSE	0	LANDESBANKHESSEN-THUERINGENGIR	0.36620745	776770000	20.47065485	2059100	14.53777955	143751	11.87583792
2014	SGLCARBONSE	0	LANDESBANKHESSEN-THUERINGENGIR	0.36619514	636011000	20.27072642	2170300	14.59037596	143291	11.87263281
2015	SGLCARBONSE	1	LANDESBANKHESSEN-THUERINGENGIR	0.38947845	771404000	20.46372279	1856100	14.43398807	149323	11.91386702
2016	SGLCARBONSE	0	LANDESBANKHESSEN-THUERINGENGIR	0.4127776	1020081000	20.74314787	1899200	14.4569433	155024	11.95133522
2017	SGLCARBONSE	0	LANDESBANKHESSEN-THUERINGENGIR	0.4159004	1460111000	21.1017783	1541700	14.24839626	160125	11.98371004
2018	SGLCARBONSE	0	LANDESBANKHESSEN-THUERINGENGIR	0.40908645	1347023000	21.02116281	1585100	14.27615805	187192	12.13989011
2019	SGLCARBONSE	0	LANDESBANKHESSEN-THUERINGENGIR	0.35903839	851611000	20.56264041	1504800	14.22417056	207035	12.24064314
2020	SGLCARBONSE	1	LANDESBANKHESSEN-THUERINGENGIR	0.34508307	2477057000	21.630337	1258800	14.04566944	214756	12.27725778
2011	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.205291347	1277450000	20.96813174	418489	12.94440588	13031	9.475086413
2012	AEGEANAIRLINESS.A.	1	NATIONAL BANK OF GREECE SA	0.233470303	1390483000	21.05291701	397158	12.89208947	11827	9.378140332
2013	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.251509333	776770000	20.47065485	561356	13.23811056	12313	9.418410894
2014	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.26618083	636011000	20.27072642	629966	13.35342113	14339	9.570738377
2015	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.237001948	771404000	20.46372279	668834	13.41329118	15233	9.631219406
2016	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.187668091	1020081000	20.74314787	650761	13.38589773	14973	9.614003858
2017	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.314212061	1460111000	21.1017783	681581	13.43217038	20241	9.915465529
2018	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.232669251	1347023000	21.02116281	725907	13.49517719	20235	9.915169057
2019	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.300100012	851611000	20.56264041	1333449	14.10327938	19326	9.869206619
2020	AEGEANAIRLINESS.A.	0	NATIONAL BANK OF GREECE SA	0.321293881	2477057000	21.630337	1440997	14.18084579	16781	9.728002573
2011	CAFOM	0	BREDBANQUEPOPULAIRESC	0.12857026	1277450000	20.96813174	268305	12.49987967	122515	11.71598875
2012	CAFOM	0	BREDBANQUEPOPULAIRESC	0.12817142	1390483000	21.05291701	300189	12.61216756	109800	11.60641581
2013	CAFOM	0	BREDBANQUEPOPULAIRESC	0.09755621	776770000	20.47065485	290590	12.57966862	99335	11.50625326
2014	CAFOM	0	BREDBANQUEPOPULAIRESC	0.09987089	636011000	20.27072642	316201	12.66413337	107866	11.588645
2015	CAFOM	0	BREDBANQUEPOPULAIRESC	0.1052101	771404000	20.46372279	337465	12.72921708	111442	11.62125956
2016	CAFOM	1	BREDBANQUEPOPULAIRESC	0.08047221	1020081000	20.74314787	315289	12.66124496	123601	11.72481391
2017	CAFOM	1	BREDBANQUEPOPULAIRESC	0.08468787	1460111000	21.1017783	342156	12.74302205	135902	11.81968932
2018	CAFOM	0	BREDBANQUEPOPULAIRESC	0.09346004	1347023000	21.02116281	348090	12.76021635	155534	11.95461964
2019	CAFOM	0	BREDBANQUEPOPULAIRESC	0.09433707	851611000	20.56264041	347402	12.75823789	173270	12.06260635
2020	CAFOM	0	BREDBANQUEPOPULAIRESC	0.09892227	2477057000	21.630337	452258	13.02200809	200613	12.20913296
2011	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.01051429	1277450000	20.96813174	228410	12.33889754	160605	11.98670321
2012	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.01147371	1390483000	21.05291701	224289	12.32069068	153277	11.94000202
2013	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.0132841	776770000	20.47065485	447657	13.01178259	143751	11.87583792
2014	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.01499324	636011000	20.27072642	426478	12.96331606	143291	11.87263281
2015	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.01656958	771404000	20.46372279	400079	12.89941731	149323	11.91386702
2016	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.01841506	1020081000	20.74314787	463600	13.04677739	155024	11.95133522
2017	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.01863254	1460111000	21.1017783	415398	12.93699238	160125	11.98371004
2018	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.153003	1347023000	21.02116281	538764	13.19703291	187192	12.13989011
2019	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.17560497	851611000	20.56264041	496439	13.11521589	207035	12.24064314
2020	MORPHOSYSAG	0	DEUTSCHEBANKAG	0.16467272	2477057000	21.630337	1659513	14.32203474	214756	12.27725778
2011	SPORTLISBOAEBENFICA-FUTEBOLS	1	NOVOBANCO	0.37412896	1277450000	20.96813174	382078	12.85338006	12518	9.434922887
2012	SPORTLISBOAEBENFICA-FUTEBOLS	0	NOVOBANCO	0.37474556	1390483000	21.05291701	411920	12.92858443	13328	9.497622364
2013	SPORTLISBOAEBENFICA-FUTEBOLS	1	NOVOBANCO	0.39129224	776770000	20.47065485	416671	12.94005222	12969	9.470317173
2014	SPORTLISBOAEBENFICA-FUTEBOLS	1	NOVOBANCO	0.3869051	636011000	20.27072642	440679	12.996072	13763	9.529739111
2015	SPORTLISBOAEBENFICA-FUTEBOLS	0	NOVOBANCO	0.35273175	771404000	20.46372279	430210	12.97202874	14172	9.559023466
2016	SPORTLISBOAEBENFICA-FUTEBOLS	1	NOVOBANCO	0.33410354	1020081000	20.74314787	476378	13.07396694	12211	9.410092464
2017	SPORTLISBOAEBENFICA-FUTEBOLS	0	NOVOBANCO	0.29789094	1460111000	21.1017783	506065	13.1344204	11002	9.305832353
2018	SPORTLISBOAEBENFICA-FUTEBOLS	1	NOVOBANCO	0.29318324	1347023000	21.02116281	485077	13.09206292	10481	9.257319373
2019	SPORTLISBOAEBENFICA-FUTEBOLS	1	NOVOBANCO	0.2781665	851611000	20.56264041	500780	13.12392216	9813	9.191463316
2020	SPORTLISBOAEBENFICA-FUTEBOLS	0	NOVOBANCO	0.26630636	2477057000	21.630337	487066	13.09615492	9106	9.116688816
2011	WERELDHAVENV	1	ABNAMROBANKNV	0.21432916	1277450000	20.96813174	3217927	14.98424792	22256	10.01036691
2012	WERELDHAVENV	0	ABNAMROBANKNV	0.21858138	1390483000	21.05291701	3002135	14.91483426	24052	10.08797343
2013	WERELDHAVENV	0	ABNAMROBANKNV	0.33266563	776770000	20.47065485	2325876	14.6596073	23293	10.05590817
2014	WERELDHAVENV	1	ABNAMROBANKNV	0.32198246	636011000	20.27072642	3528611	15.07641487	23970	10.08455833
2015	WERELDHAVENV	0	ABNAMROBANKNV	0.33137653	771404000	20.46372279	3919762	15.1815415	23530	10.06603148
2016	WERELDHAVENV	1	ABNAMROBANKNV	0.29982463	1020081000	20.74314787	3948086	15.18874146	26259	10.17576407
2017	WERELDHAVENV	0	ABNAMROBANKNV	0.29748901	1460111000	21.1017783	3924056	15.18263637	26191	10.17317112
2018	WERELDHAVENV	0	ABNAMROBANKNV	0.29053664	1347023000	21.02116281	3510440	15.07125194	28887	10.27114695
2019	WERELDHAVENV	1	ABNAMROBANKNV	0.27954796	851611000	20.56264041	3043192	14.92841752	30140	10.31360847
2020	WERELDHAVENV	0	ABNAMROBANKNV	0.23177106	2477057000	21.630337	2742746	14.82447017	30997	10.3416457
2011	GRUPOAMPERSA	1	BancoSantander	0.00773695	1277450000	20.96813174	441215	12.99728756	111780	11.62428793
2012	GRUPOAMPERSA	1	BancoSantander	0.00685152	1390483000	21.05291701	418180	12.94366724	136345	11.82294372
2013	GRUPOAMPERSA	0	BancoSantander	0.0065435	776770000	20.47065485	336820	12.72730394	101715	11.52993006
2014	GRUPOAMPERSA	1	BancoSantander	0.00575932	636011000	20.27072642	168075	12.03216559	111810	11.62455628
2015	GRUPOAMPERSA	1	BancoSantander	0.01373166	771404000	20.46372279	172658	12.05906804	104503	11.55697106
2016	GRUPOAMPERSA	0	BancoSantander	0.01778101	1020081000	20.74314787	147273	11.90004329	101740	11.53017582
2017	GRUPOAMPERSA	1	BancoSantander	0.02027757	1460111000	21.1017783	184256	12.12408137	93758	11.44847227
2018	GRUPOAMPERSA	0	BancoSantander	0.0228203	1347023000	21.02116281	139555	11.84621407	92595	11.43599042
2019	GRUPOAMPERSA	1	BancoSantander	0.02479354	851611000	20.56264041	198799	12.20004954	89276	11.39948797
2020	GRUPOAMPERSA	1	BancoSantander	0.02483607	2477057000	21.630337	239357	12.38571144	95055	11.46221095
2011	ILSOLE24ORESPA	1	INTESASANPAOLO	0.01835046	1277450000	20.96813174	555537	13.22769049	131207	11.78453151
2012	ILSOLE24ORESPA	0	INTESASANPAOLO	0.01859165	1390483000	21.05291701	507323	13.13690316	124349	11.73084741
2013	ILSOLE24ORESPA	0	INTESASANPAOLO	0.01859543	776770000	20.47065485	456650	13.03167251	104534	11.55726766
2014	ILSOLE24ORESPA	1	INTESASANPAOLO	0.01762457	636011000	20.27072642	377319	12.84084626	93057	11.44096749
2015	ILSOLE24ORESPA	0	INTESASANPAOLO	0.01727723	771404000	20.46372279	362161	12.79984414	90070	11.40834242
2016	ILSOLE24ORESPA	0	INTESASANPAOLO	0.014862	1020081000	20.74314787	267334	12.49625409	97105	11.48354815
2017	ILSOLE24ORESPA	0	INTESASANPAOLO	0.01410158	1460111000	21.1017783	253144	12.44171378	92578	11.43580681
2018	ILSOLE24ORESPA	0	INTESASANPAOLO	0.0142081	1347023000	21.02116281	218147	12.29292443	101800	11.53076538

2019	ILSOLE24ORESPA	0	INTESASANPAOLO	0.01255725	851611000	20.56264041	213589	12.27180889	101838	11.53113859
2020	ILSOLE24ORESPA	0	INTESASANPAOLO	0.01152886	2477057000	21.630337	274384	12.52228386	122385	11.71492709
2011	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.49920438	1277450000	20.96813174	306782	12.63389268	13031	9.475086413
2012	ELGEKAS.A	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.36549021	1390483000	21.05291701	281127	12.5465618	11827	9.378140332
2013	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.37621831	776770000	20.47065485	233681	12.36171222	12313	9.418410894
2014	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3671739	636011000	20.27072642	207667	12.24369111	14339	9.570738377
2015	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36730786	771404000	20.46372279	184352	12.12460225	15233	9.631219406
2016	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3820984	1020081000	20.74314787	165343	12.01577738	14973	9.614003858
2017	ELGEKAS.A	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.38408386	1460111000	21.1017783	151006	11.92507485	20241	9.915465529
2018	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36174393	1347023000	21.02116281	143069	11.87108231	20235	9.915169057
2019	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3170243	851611000	20.56264041	157431	11.96674255	19326	9.869206619
2020	ELGEKAS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.29822514	2477057000	21.630337	152944	11.93782712	16781	9.728002573
2011	QUABITINMOBILIARIAS.A	1	DEUTSCHEBANKAG	0.01051429	1277450000	20.96813174	1607219	14.29001591	111780	11.62428793
2012	QUABITINMOBILIARIAS.A	0	DEUTSCHEBANKAG	0.01147371	1390483000	21.05291701	1074176	13.88706441	136345	11.82294372
2013	QUABITINMOBILIARIAS.A	0	DEUTSCHEBANKAG	0.0132841	776770000	20.47065485	689341	13.44349135	101715	11.52993006
2014	QUABITINMOBILIARIAS.A	0	DEUTSCHEBANKAG	0.01499324	636011000	20.27072642	463860	13.04733806	111810	11.62455628
2015	QUABITINMOBILIARIAS.A	1	DEUTSCHEBANKAG	0.01656958	771404000	20.46372279	382092	12.8534167	104503	11.55697106
2016	QUABITINMOBILIARIAS.A	0	DEUTSCHEBANKAG	0.01841506	1020081000	20.74314787	356004	12.78269725	101740	11.53017582
2017	QUABITINMOBILIARIAS.A	1	DEUTSCHEBANKAG	0.01863254	1460111000	21.1017783	528299	13.17741769	93758	11.44847227
2018	QUABITINMOBILIARIAS.A	0	DEUTSCHEBANKAG	0.153003	1347023000	21.02116281	580776	13.27212042	92595	11.43599042
2019	QUABITINMOBILIARIAS.A	1	DEUTSCHEBANKAG	0.17560497	851611000	20.56264041	731957	13.50347705	89276	11.39948797
2020	QUABITINMOBILIARIAS.A	1	DEUTSCHEBANKAG	0.16467272	2477057000	21.630337	537868	13.19536846	95055	11.46221095
2011	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.34215158	1277450000	20.96813174	431922	12.9760003	160605	11.98670321
2012	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.32669392	1390483000	21.05291701	435686	12.98467708	153277	11.94000202
2013	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.02080775	776770000	20.47065485	418085	12.94344004	143751	11.87583792
2014	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.02674141	636011000	20.27072642	394324	12.88492819	143291	11.87263281
2015	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.02518231	771404000	20.46372279	392297	12.87977448	149323	11.91386702
2016	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.01749532	1020081000	20.74314787	330146	12.70729026	155024	11.95133522
2017	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.01675886	1460111000	21.1017783	282638	12.55192221	160125	11.98371004
2018	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.27687378	1347023000	21.02116281	270393	12.50763174	187192	12.13989011
2019	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.29054854	851611000	20.56264041	256736	12.4558036	207035	12.24064314
2020	KHDHUMBOLDTWEDAGINTERNATIOI	0	ERSTEGROUPBANKAG	0.27066693	2477057000	21.630337	258923	12.464286	214756	12.27725778
2011	BASWAREOYJ	0	INGBANKNV	0.15835991	1277450000	20.96813174	121966	11.7114976	6230	8.737131612
2012	BASWAREOYJ	1	INGBANKNV	0.17459943	1390483000	21.05291701	129758	11.77342646	6514	8.781708986
2013	BASWAREOYJ	0	INGBANKNV	0.17910499	776770000	20.47065485	127043	11.75228089	6940	8.845057054
2014	BASWAREOYJ	0	INGBANKNV	0.18223707	636011000	20.27072642	168781	12.0363573	6234	8.73777346
2015	BASWAREOYJ	0	INGBANKNV	0.31478195	771404000	20.46372279	178545	12.09259595	6648	8.802071337
2016	BASWAREOYJ	1	INGBANKNV	0.20781971	1020081000	20.74314787	227043	12.33289471	7144	8.874028123
2017	BASWAREOYJ	1	INGBANKNV	0.21151742	1460111000	21.1017783	214811	12.27751385	6593	8.793763759
2018	BASWAREOYJ	0	INGBANKNV	0.21065217	1347023000	21.02116281	215688	12.2815882	7547	8.928905412
2019	BASWAREOYJ	1	INGBANKNV	0.21304728	851611000	20.56264041	224581	12.32199172	7983	8.98506956
2020	BASWAREOYJ	1	INGBANKNV	0.18482492	2477057000	21.630337	224862	12.32324216	9688	9.178643285
2011	SIDMASTEELSA	1	EUROBANKERGASIASSERVICESANDHOL	0.39590222	1277450000	20.96813174	163987	12.00754244	13031	9.475086413
2012	SIDMASTEELSA	0	EUROBANKERGASIASSERVICESANDHOL	0.40267246	1390483000	21.05291701	145120	11.88531627	11827	9.378140332
2013	SIDMASTEELSA	0	EUROBANKERGASIASSERVICESANDHOL	0.35028227	776770000	20.47065485	132338	11.79311453	12313	9.418410894
2014	SIDMASTEELSA	0	EUROBANKERGASIASSERVICESANDHOL	0.35432612	636011000	20.27072642	126991	11.7518715	14339	9.570738377
2015	SIDMASTEELSA	0	EUROBANKERGASIASSERVICESANDHOL	0.36507009	771404000	20.46372279	120705	11.70110483	15233	9.631219406
2016	SIDMASTEELSA	0	EUROBANKERGASIASSERVICESANDHOL	0.28114463	1020081000	20.74314787	118600	11.68351177	14973	9.614003858
2017	SIDMASTEELSA	1	EUROBANKERGASIASSERVICESANDHOL	0.29465758	1460111000	21.1017783	131188	11.78438669	20241	9.915465529
2018	SIDMASTEELSA	1	EUROBANKERGASIASSERVICESANDHOL	0.31441281	1347023000	21.02116281	131201	11.78448578	20235	9.915169057
2019	SIDMASTEELSA	1	EUROBANKERGASIASSERVICESANDHOL	0.30955359	851611000	20.56264041	126775	11.75016914	19326	9.869206619
2020	SIDMASTEELSA	0	EUROBANKERGASIASSERVICESANDHOL	0.31446374	2477057000	21.630337	143515	11.87419484	16781	9.728002573
2011	VALNEVA	1	EuropeanInvestmentBank	0.50385272	1277450000	20.96813174	73083	11.19935106	122515	11.71598875
2012	VALNEVA	0	EuropeanInvestmentBank	0.51673483	1390483000	21.05291701	53667	10.89055357	109800	11.60641581
2013	VALNEVA	1	EuropeanInvestmentBank	0.55159807	776770000	20.47065485	254391	12.44662773	99335	11.50625326
2014	VALNEVA	0	EuropeanInvestmentBank	0.5354389	636011000	20.27072642	227517	12.33498024	107866	11.588645
2015	VALNEVA	0	EuropeanInvestmentBank	0.53248783	771404000	20.46372279	275187	12.52520615	111442	11.62125956
2016	VALNEVA	0	EuropeanInvestmentBank	0.52755845	1020081000	20.74314787	206884	12.23991353	123601	11.72481391
2017	VALNEVA	1	EuropeanInvestmentBank	0.55726388	1460111000	21.1017783	189343	12.15131546	135902	11.81968932
2018	VALNEVA	0	EuropeanInvestmentBank	0.551466	1347023000	21.02116281	229907	12.34543016	155534	11.95461964
2019	VALNEVA	1	EuropeanInvestmentBank	0.55244746	851611000	20.56264041	264723	12.48643928	173270	12.06260635
2020	VALNEVA	0	EuropeanInvestmentBank	0.55158101	2477057000	21.630337	449164	13.01514336	200613	12.20913296
2011	BIOKARPETS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.49920438	1277450000	20.96813174	162949	12.00119255	13031	9.475086413
2012	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36549021	1390483000	21.05291701	149841	11.91733001	11827	9.378140332
2013	BIOKARPETS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.37621831	776770000	20.47065485	140240	11.85111052	12313	9.418410894
2014	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3671739	636011000	20.27072642	132875	11.79716412	14339	9.570738377
2015	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36730786	771404000	20.46372279	127504	11.75590302	15233	9.631219406
2016	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3820984	1020081000	20.74314787	125749	11.74204314	14973	9.614003858
2017	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.38408386	1460111000	21.1017783	128098	11.76055087	20241	9.915465529
2018	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36174393	1347023000	21.02116281	123766	11.72614797	20235	9.915169057
2019	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3170243	851611000	20.56264041	136090	11.82107171	19326	9.869206619
2020	BIOKARPETS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.29822514	2477057000	21.630337	144044	11.87787409	16781	9.728002573
2011	JDCGROUPAG	1	HAMBURGCOMMERCIALBANKAG	0.60638971	1277450000	20.96813174	121722	11.70949504	160605	11.98670321
2012	JDCGROUPAG	0	HAMBURGCOMMERCIALBANKAG	0.56076291	1390483000	21.05291701	93265	11.44320018	153277	11.94000202
2013	JDCGROUPAG	1	HAMBURGCOMMERCIALBANKAG	0.55821136	776770000	20.47065485	78162	11.26653887	143751	11.87583792
2014	JDCGROUPAG	0	HAMBURGCOMMERCIALBANKAG	0.54250468	636011000	20.27072642	60336	11.00768422	143291	11.87263281
2015	JDCGROUPAG	0	HAMBURGCOMMERCIALBANKAG	0.51286441	771404000	20.46372279	65802	11.09440551	149323	11.91386702
2016	JDCGROUPAG	1	HAMBURGCOMMERCIALBANKAG	0.53227049	1020081000	20.74314787	72922	11.19714566	155024	11.95133522
2017	JDCGROUPAG	1	HAMBURGCOMMERCIALBANKAG	0.49126197	1460111000	21.1017783	75157	11.22733454	160125	11.98371004
2018	JDCGROUPAG	0	HAMBURGCOMMERCIALBANKAG	0.5158651	1347023000	21.02116281	85547	11.35682121	187192	12.13989011

2019	JDCGROUPAG	0	HAMBURGCOMMERCIALBANKAG	0.57591382	851611000	20.56264041	102295	11.53561607	207035	12.24064314
2020	JDCGROUPAG	1	HAMBURGCOMMERCIALBANKAG	0.61156292	2477057000	21.630337	91791	11.42726953	214756	12.27725778
2011	REKAINDUSTRIALOYJ	1	Nordea	0.25846953	1277450000	20.96813174	97900	11.49170183	6230	8.737131612
2012	REKAINDUSTRIALOYJ	0	Nordea	0.27354088	1390483000	21.05291701	62949	11.05008015	6514	8.781708986
2013	REKAINDUSTRIALOYJ	0	Nordea	0.29374843	776770000	20.47065485	47227	10.76272104	6940	8.845057054
2014	REKAINDUSTRIALOYJ	0	Nordea	0.21782138	636011000	20.27072642	44731	10.70842205	6234	8.73777346
2015	REKAINDUSTRIALOYJ	0	Nordea	0.22457132	771404000	20.46372279	49216	10.80397405	6648	8.802071337
2016	REKAINDUSTRIALOYJ	0	Nordea	0.21730861	1020081000	20.74314787	44175	10.6959143	7144	8.874028123
2017	REKAINDUSTRIALOYJ	1	Nordea	0.22796297	1460111000	21.1017783	43242	10.67456752	6593	8.793763759
2018	REKAINDUSTRIALOYJ	0	Nordea	0.24150538	1347023000	21.02116281	46278	10.74242197	7547	8.928905412
2019	REKAINDUSTRIALOYJ	1	Nordea	0.26722454	851611000	20.56264041	58943	10.98432615	7983	8.98506956
2020	REKAINDUSTRIALOYJ	1	Nordea	0.25168973	2477057000	21.630337	73150	11.20026741	9688	9.178643285
2011	HANSEYACHTSAG	1	HAMBURGCOMMERCIALBANKAG	0.60638971	1277450000	20.96813174	62600	11.04452056	160605	11.98670321
2012	HANSEYACHTSAG	0	HAMBURGCOMMERCIALBANKAG	0.56076291	1390483000	21.05291701	59601	10.99542763	153277	11.94000202
2013	HANSEYACHTSAG	1	HAMBURGCOMMERCIALBANKAG	0.55821136	776770000	20.47065485	54108	10.89873733	143751	11.87583792
2014	HANSEYACHTSAG	0	HAMBURGCOMMERCIALBANKAG	0.54250468	636011000	20.27072642	67236	11.1159641	143291	11.87263281
2015	HANSEYACHTSAG	0	HAMBURGCOMMERCIALBANKAG	0.51286441	771404000	20.46372279	58839	10.98256018	149323	11.91386702
2016	HANSEYACHTSAG	0	HAMBURGCOMMERCIALBANKAG	0.53227049	1020081000	20.74314787	64306	11.07140822	155024	11.95133522
2017	HANSEYACHTSAG	0	HAMBURGCOMMERCIALBANKAG	0.49126197	1460111000	21.1017783	69786	11.1531887	160125	11.98371004
2018	HANSEYACHTSAG	1	HAMBURGCOMMERCIALBANKAG	0.5158651	1347023000	21.02116281	91477	11.42384285	187192	12.13989011
2019	HANSEYACHTSAG	0	HAMBURGCOMMERCIALBANKAG	0.57591382	851611000	20.56264041	97347	11.48603719	207035	12.24064314
2020	HANSEYACHTSAG	0	HAMBURGCOMMERCIALBANKAG	0.61156292	2477057000	21.630337	95861	11.4706545	214756	12.27725778
2011	CALTAGIRONEEDITORES.P.A.	1	BANCAMONTEDEIPASCHIDISIENASPA	0.00652075	1277450000	20.96813174	949170	13.7633432	131207	11.78453151
2012	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.0076053	1390483000	21.05291701	892115	13.70135033	124349	11.73084741
2013	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.00609966	776770000	20.47065485	841107	13.64247416	104534	11.55726766
2014	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.00511828	636011000	20.27072642	774246	13.55964493	93057	11.44096749
2015	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.00504619	771404000	20.46372279	739648	13.51392968	90070	11.40834242
2016	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.00581507	1020081000	20.74314787	628235	13.35066958	97105	11.48354815
2017	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.00635529	1460111000	21.1017783	581187	13.27282784	92578	11.43580681
2018	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.00730714	1347023000	21.02116281	543993	13.20669166	101800	11.53076538
2019	CALTAGIRONEEDITORES.P.A.	1	BANCAMONTEDEIPASCHIDISIENASPA	0.00827314	851611000	20.56264041	538174	13.19593721	101838	11.53113859
2020	CALTAGIRONEEDITORES.P.A.	0	BANCAMONTEDEIPASCHIDISIENASPA	0.00720948	2477057000	21.630337	450155	13.01734725	122385	11.71492709
2011	INCAPOYJ	0	AKTIABANKPLC	0.08121113	1277450000	20.96813174	39271	10.57824161	6230	8.737131612
2012	INCAPOYJ	0	AKTIABANKPLC	0.06979036	1390483000	21.05291701	29283	10.28476242	6514	8.781708986
2013	INCAPOYJ	0	AKTIABANKPLC	0.04947472	776770000	20.47065485	15782	9.666625329	6940	8.845057054
2014	INCAPOYJ	0	AKTIABANKPLC	0.03924071	636011000	20.27072642	14394	9.574566732	6234	8.73777346
2015	INCAPOYJ	1	AKTIABANKPLC	0.06438671	771404000	20.46372279	18124	9.804992306	6648	8.802071337
2016	INCAPOYJ	0	AKTIABANKPLC	0.09303142	1020081000	20.74314787	21683	9.984283822	7144	8.874028123
2017	INCAPOYJ	0	AKTIABANKPLC	0.11736052	1460111000	21.1017783	24780	10.11779216	6593	8.793763759
2018	INCAPOYJ	0	AKTIABANKPLC	0.14535721	1347023000	21.02116281	32080	10.37598806	7547	8.928905412
2019	INCAPOYJ	0	AKTIABANKPLC	0.1588104	851611000	20.56264041	36475	10.50438237	7983	8.98506956
2020	INCAPOYJ	1	AKTIABANKPLC	0.18103112	2477057000	21.630337	76365	11.24327976	9688	9.178643285
2011	WOLFORDAG	0	UNICREDITSPA	0.01235034	1277450000	20.96813174	144458	11.88074409	20099	9.908425342
2012	WOLFORDAG	0	UNICREDITSPA	0.0121574	1390483000	21.05291701	145460	11.88765641	19163	9.860736615
2013	WOLFORDAG	0	UNICREDITSPA	0.01247691	776770000	20.47065485	142316	11.86580522	18290	9.814109741
2014	WOLFORDAG	0	UNICREDITSPA	0.01222994	636011000	20.27072642	138119	11.83587091	13397	9.50278608
2015	WOLFORDAG	0	UNICREDITSPA	0.01129295	771404000	20.46372279	147437	11.90115624	12545	9.437077459
2016	WOLFORDAG	0	UNICREDITSPA	0.01184398	1020081000	20.74314787	137467	11.83113917	12275	9.415319953
2017	WOLFORDAG	0	UNICREDITSPA	0.01316751	1460111000	21.1017783	138386	11.83780216	12643	9.444858981
2018	WOLFORDAG	0	UNICREDITSPA	0.01705056	1347023000	21.02116281	114328	11.64682679	19888	9.897871814
2019	WOLFORDAG	0	UNICREDITSPA	0.01604634	851611000	20.56264041	117988	11.6783382	21311	9.96697865
2020	WOLFORDAG	0	UNICREDITSPA	0.01313642	2477057000	21.630337	161689	11.99343002	22807	10.03482279
2011	ELASTRONS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.49920438	1277450000	20.96813174	144059	11.87797822	13031	9.475086413
2012	ELASTRONS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36549021	1390483000	21.05291701	124224	11.72984167	11827	9.378140332
2013	ELASTRONS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.37621831	776770000	20.47065485	102641	11.53899274	12313	9.418410894
2014	ELASTRONS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3671739	636011000	20.27072642	112845	11.63377047	14339	9.570738377
2015	ELASTRONS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36730786	771404000	20.46372279	96460	11.47688369	15233	9.631219406
2016	ELASTRONS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3820984	1020081000	20.74314787	105107	11.56273416	14973	9.614003858
2017	ELASTRONS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.38408386	1460111000	21.1017783	129328	11.77010709	20241	9.915465529
2018	ELASTRONS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.36174393	1347023000	21.02116281	125173	11.73745206	20235	9.915169057
2019	ELASTRONS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.3170243	851611000	20.56264041	126847	11.75073691	19326	9.869206619
2020	ELASTRONS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.29822514	2477057000	21.630337	128719	11.76538701	16781	9.728002573
2011	SOCIETEDELATOUREIFFEL	1	SOCIETEGENERALE	0.07274	1277450000	20.96813174	1043277	13.85787728	122515	11.71598875
2012	SOCIETEDELATOUREIFFEL	0	SOCIETEGENERALE	0.06405365	1390483000	21.05291701	954734	13.76918805	109800	11.60641581
2013	SOCIETEDELATOUREIFFEL	0	SOCIETEGENERALE	0.06153635	776770000	20.47065485	758468	13.53905589	99335	11.50625326
2014	SOCIETEDELATOUREIFFEL	1	SOCIETEGENERALE	0.05462268	636011000	20.27072642	662184	13.40329874	107866	11.588645
2015	SOCIETEDELATOUREIFFEL	1	SOCIETEGENERALE	0.05472084	771404000	20.46372279	843699	13.64555107	111442	11.62125956
2016	SOCIETEDELATOUREIFFEL	1	SOCIETEGENERALE	0.05439811	1020081000	20.74314787	1000045	13.81555556	123601	11.72481391
2017	SOCIETEDELATOUREIFFEL	0	SOCIETEGENERALE	0.05908426	1460111000	21.1017783	1005888	13.82138129	135902	11.81968932
2018	SOCIETEDELATOUREIFFEL	0	SOCIETEGENERALE	0.06017437	1347023000	21.02116281	1674016	14.33073609	155534	11.95461964
2019	SOCIETEDELATOUREIFFEL	0	SOCIETEGENERALE	0.05894972	851611000	20.56264041	1722021	14.35900916	173270	12.06260635
2020	SOCIETEDELATOUREIFFEL	0	SOCIETEGENERALE	0.0560162	2477057000	21.630337	1828875	14.41921158	200613	12.20913296
2011	AMBIENTHESISS.P.A.	1	INTESASANPAOLO	0.01835046	1277450000	20.96813174	146676	11.89598135	131207	11.78453151
2012	AMBIENTHESISS.P.A.	0	INTESASANPAOLO	0.01859165	1390483000	21.05291701	139179	11.84351615	124349	11.73084741
2013	AMBIENTHESISS.P.A.	1	INTESASANPAOLO	0.01859543	776770000	20.47065485	136827	11.82647263	104534	11.55726766
2014	AMBIENTHESISS.P.A.	0	INTESASANPAOLO	0.01762457	636011000	20.27072642	129864	11.77424303	93057	11.44096749
2015	AMBIENTHESISS.P.A.	0	INTESASANPAOLO	0.01727723	771404000	20.46372279	115318	11.65544881	90070	11.40834242
2016	AMBIENTHESISS.P.A.	1	INTESASANPAOLO	0.014862	1020081000	20.74314787	109254	11.60143073	97105	11.48354815
2017	AMBIENTHESISS.P.A.	0	INTESASANPAOLO	0.01410158	1460111000	21.1017783	103908	11.55126117	92578	11.43580681
2018	AMBIENTHESISS.P.A.	0	INTESASANPAOLO	0.0142081	1347023000	21.02116281	96770	11.48009231	101800	11.53076538

2019	AMBIENTHESISS.P.A.	1	INTESASANPAOLO	0.01255725	851611000	20.56264041	110561	11.61332268	101838	11.53113859
2020	AMBIENTHESISS.P.A.	1	INTESASANPAOLO	0.01152886	2477057000	21.630337	133503	11.80187923	122385	11.71492709
2011	NSINV	0	INGBANKNV	0.15835991	1277450000	20.96813174	2352568	14.67101806	22256	10.01036691
2012	NSINV	0	INGBANKNV	0.17459943	1390483000	21.05291701	2147915	14.58000816	24052	10.08797343
2013	NSINV	0	INGBANKNV	0.17910499	776770000	20.47065485	1847843	14.42952957	23293	10.05590817
2014	NSINV	0	INGBANKNV	0.18223707	636011000	20.27072642	1700186	14.34624821	23970	10.08455833
2015	NSINV	0	INGBANKNV	0.31478195	771404000	20.46372279	1288544	14.06902346	23530	10.06603148
2016	NSINV	0	INGBANKNV	0.20781971	1020081000	20.74314787	1166462	13.96948579	26259	10.17576407
2017	NSINV	0	INGBANKNV	0.21151742	1460111000	21.1017783	1118269	13.92729251	26191	10.17317112
2018	NSINV	0	INGBANKNV	0.21065217	1347023000	21.02116281	1216559	14.01153694	28887	10.27114695
2019	NSINV	0	INGBANKNV	0.21304728	851611000	20.56264041	1291133	14.07103069	30140	10.31360847
2020	NSINV	0	INGBANKNV	0.18482492	2477057000	21.630337	1258103	14.04511559	30997	10.3416457
2011	NURMINENLOGISTICSOYJ	1	OMASAASTOPANKKI	0.2170454	1277450000	20.96813174	69354	11.1469791	6230	8.737131612
2012	NURMINENLOGISTICSOYJ	1	OMASAASTOPANKKI	0.24270687	1390483000	21.05291701	69772	11.15298806	6514	8.781708986
2013	NURMINENLOGISTICSOYJ	0	OMASAASTOPANKKI	0.2206063	776770000	20.47065485	57486	10.95929672	6940	8.845057054
2014	NURMINENLOGISTICSOYJ	0	OMASAASTOPANKKI	0.17774804	636011000	20.27072642	45299	10.72104024	6234	8.73777346
2015	NURMINENLOGISTICSOYJ	1	OMASAASTOPANKKI	0.17140568	771404000	20.46372279	51033	10.84022776	6648	8.802071337
2016	NURMINENLOGISTICSOYJ	0	OMASAASTOPANKKI	0.17139875	1020081000	20.74314787	43854	10.68862121	7144	8.874028123
2017	NURMINENLOGISTICSOYJ	1	OMASAASTOPANKKI	0.1714369	1460111000	21.1017783	47587	10.77031489	6593	8.793763759
2018	NURMINENLOGISTICSOYJ	0	OMASAASTOPANKKI	0.26984482	1347023000	21.02116281	41511	10.63371373	7547	8.928905412
2019	NURMINENLOGISTICSOYJ	0	OMASAASTOPANKKI	0.26899833	851611000	20.56264041	52088	10.86068987	7983	8.98506956
2020	NURMINENLOGISTICSOYJ	1	OMASAASTOPANKKI	0.25273015	2477057000	21.630337	66179	11.10011847	9688	9.178643285
2011	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.49920438	1277450000	20.96813174	31998	10.37342868	13031	9.475086413
2012	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36549021	1390483000	21.05291701	23829	10.07865861	11827	9.378140332
2013	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.37621831	776770000	20.47065485	22777	10.03350653	12313	9.418410894
2014	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3671739	636011000	20.27072642	23211	10.05238158	14339	9.570738377
2015	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36730786	771404000	20.46372279	23771	10.07622163	15233	9.631219406
2016	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3820984	1020081000	20.74314787	25905	10.16219128	14973	9.614003858
2017	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.38408386	1460111000	21.1017783	25683	10.15358457	20241	9.915465529
2018	CARSMOTORCYCLESANDMARINEEN	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.36174393	1347023000	21.02116281	66675	11.10758535	20235	9.915169057
2019	CARSMOTORCYCLESANDMARINEEN	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.3170243	851611000	20.56264041	75921	11.2374486	19326	9.869206619
2020	CARSMOTORCYCLESANDMARINEEN	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.29822514	2477057000	21.630337	62551	11.0437375	16781	9.728002573
2011	COMPONENTAOYJ	1	OPCORPORATEBANKPLC	0.29218317	1277450000	20.96813174	436800	12.9872307	6230	8.737131612
2012	COMPONENTAOYJ	1	OPCORPORATEBANKPLC	0.29363535	1390483000	21.05291701	460400	13.03985096	6514	8.781708986
2013	COMPONENTAOYJ	0	OPCORPORATEBANKPLC	0.29342348	776770000	20.47065485	452000	13.02143746	6940	8.845057054
2014	COMPONENTAOYJ	1	OPCORPORATEBANKPLC	0.2711427	636011000	20.27072642	468900	13.05814481	6234	8.73777346
2015	COMPONENTAOYJ	0	OPCORPORATEBANKPLC	0.25844713	771404000	20.46372279	402200	12.90470476	6648	8.802071337
2016	COMPONENTAOYJ	0	OPCORPORATEBANKPLC	0.0868354	1020081000	20.74314787	84200	11.3409502	7144	8.874028123
2017	COMPONENTAOYJ	1	OPCORPORATEBANKPLC	0.09030946	1460111000	21.1017783	52800	10.87426647	6593	8.793763759
2018	COMPONENTAOYJ	1	OPCORPORATEBANKPLC	0.09809859	1347023000	21.02116281	48900	10.79753268	7547	8.928905412
2019	COMPONENTAOYJ	0	OPCORPORATEBANKPLC	0.10534543	851611000	20.56264041	54098	10.8985525	7983	8.98506956
2020	COMPONENTAOYJ	1	OPCORPORATEBANKPLC	0.09316972	2477057000	21.630337	64005	11.06671648	9688	9.178643285
2011	EUROTECHSPA	1	UNICREDITSPA	0.01235034	1277450000	20.96813174	206133	12.23627687	131207	11.78453151
2012	EUROTECHSPA	0	UNICREDITSPA	0.0121574	1390483000	21.05291701	180461	12.10326997	124349	11.73084741
2013	EUROTECHSPA	0	UNICREDITSPA	0.01247691	776770000	20.47065485	155477	11.95425309	104534	11.55726766
2014	EUROTECHSPA	1	UNICREDITSPA	0.01222994	636011000	20.27072642	143688	11.87539956	93057	11.44096749
2015	EUROTECHSPA	1	UNICREDITSPA	0.01129295	771404000	20.46372279	145453	11.88760829	90070	11.40834242
2016	EUROTECHSPA	1	UNICREDITSPA	0.01184398	1020081000	20.74314787	141970	11.86337105	97105	11.48354815
2017	EUROTECHSPA	0	UNICREDITSPA	0.01316751	1460111000	21.1017783	127242	11.75384606	92578	11.43580681
2018	EUROTECHSPA	1	UNICREDITSPA	0.01705056	1347023000	21.02116281	143547	11.87441779	101800	11.53076538
2019	EUROTECHSPA	1	UNICREDITSPA	0.01604634	851611000	20.56264041	170509	12.04654336	101838	11.53113859
2020	EUROTECHSPA	1	UNICREDITSPA	0.01313642	2477057000	21.630337	179718	12.09914423	122385	11.71492709
2011	PININFARINASPA	1	INTESASANPAOLO	0.01835046	1277450000	20.96813174	282590	12.55175236	131207	11.78453151
2012	PININFARINASPA	0	INTESASANPAOLO	0.01859165	1390483000	21.05291701	197520	12.19359512	124349	11.73084741
2013	PININFARINASPA	0	INTESASANPAOLO	0.01859543	776770000	20.47065485	157216	11.96537593	104534	11.55726766
2014	PININFARINASPA	0	INTESASANPAOLO	0.01762457	636011000	20.27072642	142354	11.86607219	93057	11.44096749
2015	PININFARINASPA	0	INTESASANPAOLO	0.01727723	771404000	20.46372279	120624	11.70043355	90070	11.40834242
2016	PININFARINASPA	0	INTESASANPAOLO	0.014862	1020081000	20.74314787	101301	11.52585156	97105	11.48354815
2017	PININFARINASPA	0	INTESASANPAOLO	0.01410158	1460111000	21.1017783	125910	11.74332264	92578	11.43580681
2018	PININFARINASPA	0	INTESASANPAOLO	0.0142081	1347023000	21.02116281	131380	11.78584917	101800	11.53076538
2019	PININFARINASPA	1	INTESASANPAOLO	0.01255725	851611000	20.56264041	121515	11.70779299	101838	11.53113859
2020	PININFARINASPA	0	INTESASANPAOLO	0.01152886	2477057000	21.630337	103193	11.5443563	122385	11.71492709
2011	GABETTIPROPERTYSOLUTIONSSPA	1	BPERBANCAS.P.A.	0.01292374	1277450000	20.96813174	179044	12.09538686	131207	11.78453151
2012	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.01235533	1390483000	21.05291701	65535	11.09033963	124349	11.73084741
2013	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.01162678	776770000	20.47065485	58896	10.98352846	104534	11.55726766
2014	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.0116141	636011000	20.27072642	61563	11.02781632	93057	11.44096749
2015	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.0115141	771404000	20.46372279	59718	10.99738876	90070	11.40834242
2016	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.01204739	1020081000	20.74314787	54876	10.91283137	97105	11.48354815
2017	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.01096765	1460111000	21.1017783	53141	10.88070404	92578	11.43580681
2018	GABETTIPROPERTYSOLUTIONSSPA	1	BPERBANCAS.P.A.	0.01214218	1347023000	21.02116281	53383	10.88524762	101800	11.53076538
2019	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.01361023	851611000	20.56264041	58362	10.97442027	101838	11.53113859
2020	GABETTIPROPERTYSOLUTIONSSPA	0	BPERBANCAS.P.A.	0.01116173	2477057000	21.630337	70206	11.15918906	122385	11.71492709
2011	PLCS.P.A.	1	UNICREDITSPA	0.01235034	1277450000	20.96813174	127110	11.75280813	131207	11.78453151
2012	PLCS.P.A.	0	UNICREDITSPA	0.0121574	1390483000	21.05291701	110410	11.61195599	124349	11.73084741
2013	PLCS.P.A.	0	UNICREDITSPA	0.01247691	776770000	20.47065485	87673	11.38136926	104534	11.55726766
2014	PLCS.P.A.	0	UNICREDITSPA	0.01222994	636011000	20.27072642	59991	11.00194983	93057	11.44096749
2015	PLCS.P.A.	1	UNICREDITSPA	0.01129295	771404000	20.46372279	42987	10.66865302	90070	11.40834242
2016	PLCS.P.A.	0	UNICREDITSPA	0.01184398	1020081000	20.74314787	30410	10.32252678	97105	11.48354815
2017	PLCS.P.A.	0	UNICREDITSPA	0.01316751	1460111000	21.1017783	45078	10.7161496	92578	11.43580681
2018	PLCS.P.A.	0	UNICREDITSPA	0.01705056	1347023000	21.02116281	67557	11.12072696	101800	11.53076538

2019	PLCS.P.A.	0	UNICREDITSPA	0.01604634	851611000	20.56264041	65432	11.08876671	101838	11.53113859
2020	PLCS.P.A.	1	UNICREDITSPA	0.01313642	2477057000	21.630337	71189	11.17309359	122385	11.71492709
2011	SOLARIAENERGIAYMEDIOAMBIENTE	1	NATIXISSA	0.02943598	1277450000	20.96813174	394898	12.88638278	111780	11.62428793
2012	SOLARIAENERGIAYMEDIOAMBIENTE	0	NATIXISSA	0.01504321	1390483000	21.05291701	312355	12.65189564	136345	11.82294372
2013	SOLARIAENERGIAYMEDIOAMBIENTE	0	NATIXISSA	0.01814632	776770000	20.47065485	222258	12.31159415	101715	11.52993006
2014	SOLARIAENERGIAYMEDIOAMBIENTE	0	NATIXISSA	0.02043108	636011000	20.27072642	197274	12.1923489	111810	11.62455628
2015	SOLARIAENERGIAYMEDIOAMBIENTE	0	NATIXISSA	0.03445429	771404000	20.46372279	172228	12.05657446	104503	11.55697106
2016	SOLARIAENERGIAYMEDIOAMBIENTE	0	NATIXISSA	0.03692084	1020081000	20.74314787	190301	12.15636231	101740	11.53017582
2017	SOLARIAENERGIAYMEDIOAMBIENTE	1	NATIXISSA	0.03567589	1460111000	21.1017783	280887	12.54570773	93758	11.44847227
2018	SOLARIAENERGIAYMEDIOAMBIENTE	1	NATIXISSA	0.02882768	1347023000	21.02116281	394670	12.88580525	92595	11.43599042
2019	SOLARIAENERGIAYMEDIOAMBIENTE	1	NATIXISSA	0.02362336	851611000	20.56264041	600526	13.30556122	89276	11.39948797
2020	SOLARIAENERGIAYMEDIOAMBIENTE	1	NATIXISSA	0.02042316	2477057000	21.630337	715507	13.48074666	95055	11.46221095
2011	DEUTSCHEROHSTOFFAG	1	UNICREDITSPA	0.01235034	1277450000	20.96813174	40168	10.60082594	160605	11.98670321
2012	DEUTSCHEROHSTOFFAG	0	UNICREDITSPA	0.0121574	1390483000	21.05291701	63451	11.05802323	153277	11.94000202
2013	DEUTSCHEROHSTOFFAG	1	UNICREDITSPA	0.01247691	776770000	20.47065485	131533	11.78701305	143751	11.87583792
2014	DEUTSCHEROHSTOFFAG	0	UNICREDITSPA	0.01222994	636011000	20.27072642	134696	11.81077567	143291	11.87263281
2015	DEUTSCHEROHSTOFFAG	1	UNICREDITSPA	0.01129295	771404000	20.46372279	128054	11.76020733	149323	11.91386702
2016	DEUTSCHEROHSTOFFAG	1	UNICREDITSPA	0.01184398	1020081000	20.74314787	193472	12.17288808	155024	11.95133522
2017	DEUTSCHEROHSTOFFAG	1	UNICREDITSPA	0.01316751	1460111000	21.1017783	213574	12.27173866	160125	11.98371004
2018	DEUTSCHEROHSTOFFAG	0	UNICREDITSPA	0.01705056	1347023000	21.02116281	224845	12.32316655	187192	12.13989011
2019	DEUTSCHEROHSTOFFAG	1	UNICREDITSPA	0.01604634	851611000	20.56264041	278925	12.53869821	207035	12.24064314
2020	DEUTSCHEROHSTOFFAG	1	UNICREDITSPA	0.01313642	2477057000	21.630337	206722	12.23913017	214756	12.27725778
2011	ENEDOOYJ	1	AKTIABANKPLC	0.08121113	1277450000	20.96813174	49874	10.8172551	6230	8.737131612
2012	ENEDOOYJ	0	AKTIABANKPLC	0.06979036	1390483000	21.05291701	43311	10.67616192	6514	8.781708986
2013	ENEDOOYJ	1	AKTIABANKPLC	0.04947472	776770000	20.47065485	58476	10.97637169	6940	8.845057054
2014	ENEDOOYJ	0	AKTIABANKPLC	0.03924071	636011000	20.27072642	56598	10.94372893	6234	8.73777346
2015	ENEDOOYJ	0	AKTIABANKPLC	0.06438671	771404000	20.46372279	55632	10.92651385	6648	8.802071337
2016	ENEDOOYJ	0	AKTIABANKPLC	0.09303142	1020081000	20.74314787	48327	10.78574569	7144	8.874028123
2017	ENEDOOYJ	1	AKTIABANKPLC	0.11736052	1460111000	21.1017783	39350	10.58025125	6593	8.793763759
2018	ENEDOOYJ	1	AKTIABANKPLC	0.14535721	1347023000	21.02116281	45690	10.72963473	7547	8.928905412
2019	ENEDOOYJ	1	AKTIABANKPLC	0.1588104	851611000	20.56264041	32122	10.37729643	7983	8.98506956
2020	ENEDOOYJ	1	AKTIABANKPLC	0.18103112	2477057000	21.630337	29153	10.2803131	9688	9.178643285
2011	LAVIPHARMS.A.	0	ATTICABANKSA	0.67281248	1277450000	20.96813174	145672	11.8891128	13031	9.475086413
2012	LAVIPHARMS.A.	0	ATTICABANKSA	0.616628	1390483000	21.05291701	120430	11.69882395	11827	9.378140332
2013	LAVIPHARMS.A.	0	ATTICABANKSA	0.631731	776770000	20.47065485	108036	11.59021978	12313	9.418410894
2014	LAVIPHARMS.A.	0	ATTICABANKSA	0.65444599	636011000	20.27072642	83824	11.33647464	14339	9.570738377
2015	LAVIPHARMS.A.	0	ATTICABANKSA	0.76324458	771404000	20.46372279	82379	11.31908583	15233	9.631219406
2016	LAVIPHARMS.A.	0	ATTICABANKSA	0.79452306	1020081000	20.74314787	48177	10.78263701	14973	9.614003858
2017	LAVIPHARMS.A.	0	ATTICABANKSA	0.53360967	1460111000	21.1017783	44808	10.71014197	20241	9.915465529
2018	LAVIPHARMS.A.	0	ATTICABANKSA	0.35588755	1347023000	21.02116281	41897	10.6429695	20235	9.915169057
2019	LAVIPHARMS.A.	0	ATTICABANKSA	0.34148493	851611000	20.56264041	49422	10.80815095	19326	9.869206619
2020	LAVIPHARMS.A.	0	ATTICABANKSA	0.37613509	2477057000	21.630337	50638	10.83245756	16781	9.728002573
2011	BASTOGISPA	1	CASSADEPOSITIEPRESTITI	0.00389011	1277450000	20.96813174	58713	10.98041645	131207	11.78453151
2012	BASTOGISPA	0	CASSADEPOSITIEPRESTITI	0.00339983	1390483000	21.05291701	53380	10.88519142	124349	11.73084741
2013	BASTOGISPA	0	CASSADEPOSITIEPRESTITI	0.00391802	776770000	20.47065485	48754	10.79454252	104534	11.55726766
2014	BASTOGISPA	0	CASSADEPOSITIEPRESTITI	0.00316347	636011000	20.27072642	47316	10.76460378	93057	11.44096749
2015	BASTOGISPA	1	CASSADEPOSITIEPRESTITI	0.00427778	771404000	20.46372279	470144	13.06079431	90070	11.40834242
2016	BASTOGISPA	0	CASSADEPOSITIEPRESTITI	0.00461449	1020081000	20.74314787	445072	13.00599135	97105	11.48354815
2017	BASTOGISPA	1	CASSADEPOSITIEPRESTITI	0.00390036	1460111000	21.1017783	459956	13.03888611	92578	11.43580681
2018	BASTOGISPA	1	CASSADEPOSITIEPRESTITI	0.00298021	1347023000	21.02116281	386915	12.86596031	101800	11.53076538
2019	BASTOGISPA	0	CASSADEPOSITIEPRESTITI	0.00324173	851611000	20.56264041	378968	12.84520705	101838	11.53113859
2020	BASTOGISPA	1	CASSADEPOSITIEPRESTITI	0.00361019	2477057000	21.630337	393687	12.88331146	122385	11.71492709
2011	BIOFRONTERAAG	0	EuropeanInvestmentBank	0.50385272	1277450000	20.96813174	5697	8.647694999	160605	11.98670321
2012	BIOFRONTERAAG	0	EuropeanInvestmentBank	0.51673483	1390483000	21.05291701	9035	9.108861203	153277	11.94000202
2013	BIOFRONTERAAG	0	EuropeanInvestmentBank	0.55159807	776770000	20.47065485	9637	9.173365136	143751	11.87583792
2014	BIOFRONTERAAG	0	EuropeanInvestmentBank	0.5354389	636011000	20.27072642	14010	9.547526639	143291	11.87263281
2015	BIOFRONTERAAG	0	EuropeanInvestmentBank	0.53248783	771404000	20.46372279	9498	9.158836529	149323	11.91386702
2016	BIOFRONTERAAG	0	EuropeanInvestmentBank	0.52755845	1020081000	20.74314787	23879	10.08075469	155024	11.95133522
2017	BIOFRONTERAAG	1	EuropeanInvestmentBank	0.55726388	1460111000	21.1017783	19848	9.895858525	160125	11.98371004
2018	BIOFRONTERAAG	1	EuropeanInvestmentBank	0.551466	1347023000	21.02116281	39133	10.57472138	187192	12.13989011
2019	BIOFRONTERAAG	1	EuropeanInvestmentBank	0.55244746	851611000	20.56264041	58363	10.97443741	207035	12.24064314
2020	BIOFRONTERAAG	1	EuropeanInvestmentBank	0.55158101	2477057000	21.630337	56391	10.94006485	214756	12.27725778
2011	HFCOMPANY	1	COOPERATIEVERABOBANKU.A.	0.23963417	1277450000	20.96813174	143278	11.87254208	122515	11.71598875
2012	HFCOMPANY	0	COOPERATIEVERABOBANKU.A.	0.2347648	1390483000	21.05291701	113431	11.63895	109800	11.60641581
2013	HFCOMPANY	0	COOPERATIEVERABOBANKU.A.	0.25328437	776770000	20.47065485	107594	11.58612016	99335	11.50625326
2014	HFCOMPANY	0	COOPERATIEVERABOBANKU.A.	0.23370159	636011000	20.27072642	93068	11.44108569	107866	11.588645
2015	HFCOMPANY	0	COOPERATIEVERABOBANKU.A.	0.24746902	771404000	20.46372279	89688	11.40409226	111442	11.62125956
2016	HFCOMPANY	1	COOPERATIEVERABOBANKU.A.	0.54505981	1020081000	20.74314787	73877	11.21015683	123601	11.72481391
2017	HFCOMPANY	0	COOPERATIEVERABOBANKU.A.	0.59072353	1460111000	21.1017783	63304	11.0557038	135902	11.81968932
2018	HFCOMPANY	0	COOPERATIEVERABOBANKU.A.	0.61421131	1347023000	21.02116281	56407	10.94034854	155534	11.95461964
2019	HFCOMPANY	0	COOPERATIEVERABOBANKU.A.	0.62507195	851611000	20.56264041	53810	10.8932146	173270	12.06260635
2020	HFCOMPANY	1	COOPERATIEVERABOBANKU.A.	0.58011185	2477057000	21.630337	47167	10.76144977	200613	12.20913296
2011	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.01051429	1277450000	20.96813174	51048	10.84052165	160605	11.98670321
2012	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.01147371	1390483000	21.05291701	37175	10.52339177	153277	11.94000202
2013	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.0132841	776770000	20.47065485	26879	10.19910059	143751	11.87583792
2014	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.01499324	636011000	20.27072642	27821	10.23354641	143291	11.87263281
2015	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.01656958	771404000	20.46372279	28150	10.24530263	149323	11.91386702
2016	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.01841506	1020081000	20.74314787	27618	10.22622301	155024	11.95133522
2017	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.01863254	1460111000	21.1017783	26462	10.18346502	160125	11.98371004
2018	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.153003	1347023000	21.02116281	29504	10.29228113	187192	12.13989011

2019	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.17560497	851611000	20.56264041	104838	11.56017158	207035	12.24064314
2020	LLOYDFONDSAG	0	DEUTSCHEBANKAG	0.16467272	2477057000	21.630337	113677	11.64111637	214756	12.27725778
2011	DIGITALISTGROUPOYJ	1	Nordea	0.25846953	1277450000	20.96813174	52970	10.87748099	6230	8.737131612
2012	DIGITALISTGROUPOYJ	0	Nordea	0.27354088	1390483000	21.05291701	33331	10.41424317	6514	8.781708986
2013	DIGITALISTGROUPOYJ	0	Nordea	0.29374843	776770000	20.47065485	25843	10.15979505	6940	8.845057054
2014	DIGITALISTGROUPOYJ	1	Nordea	0.21782138	636011000	20.27072642	21897	9.99410492	6234	8.73777346
2015	DIGITALISTGROUPOYJ	0	Nordea	0.22457132	771404000	20.46372279	18347	9.817221352	6648	8.802071337
2016	DIGITALISTGROUPOYJ	1	Nordea	0.21730861	1020081000	20.74314787	16095	9.686263944	7144	8.874028123
2017	DIGITALISTGROUPOYJ	1	Nordea	0.22796297	1460111000	21.1017783	25027	10.12771052	6593	8.793763759
2018	DIGITALISTGROUPOYJ	0	Nordea	0.24150538	1347023000	21.02116281	32222	10.38040473	7547	8.928905412
2019	DIGITALISTGROUPOYJ	0	Nordea	0.26722454	851611000	20.56264041	26280	10.17656347	7983	8.98506956
2020	DIGITALISTGROUPOYJ	0	Nordea	0.25168973	2477057000	21.630337	19645	9.885578132	9688	9.178643285
2011	VISIOMEDGROUP	0	BNPPARIBAS	0.14717988	1277450000	20.96813174	15427	9.6438745	122515	11.71598875
2012	VISIOMEDGROUP	0	BNPPARIBAS	0.05735219	1390483000	21.05291701	12913	9.465989835	109800	11.60641581
2013	VISIOMEDGROUP	0	BNPPARIBAS	0.05002956	776770000	20.47065485	12617	9.44280039	99335	11.50625326
2014	VISIOMEDGROUP	0	BNPPARIBAS	0.04196364	636011000	20.27072642	15008	9.616338671	107866	11.588645
2015	VISIOMEDGROUP	0	BNPPARIBAS	0.04329418	771404000	20.46372279	19265	9.866045257	111442	11.62125956
2016	VISIOMEDGROUP	0	BNPPARIBAS	0.044782	1020081000	20.74314787	19408	9.873440631	123601	11.72481391
2017	VISIOMEDGROUP	1	BNPPARIBAS	0.0450166	1460111000	21.1017783	20135	9.910214873	135902	11.81968932
2018	VISIOMEDGROUP	0	BNPPARIBAS	0.04780756	1347023000	21.02116281	18525	9.82687645	155534	11.95461964
2019	VISIOMEDGROUP	0	BNPPARIBAS	0.04928758	851611000	20.56264041	14731	9.597709396	173270	12.06260635
2020	VISIOMEDGROUP	0	BNPPARIBAS	0.04717422	2477057000	21.630337	5909	8.684231891	200613	12.20913296
2011	PIERRELS.P.A.	1	INTESASANPAOLO	0.01835046	1277450000	20.96813174	70231	11.15954509	131207	11.78453151
2012	PIERRELS.P.A.	0	INTESASANPAOLO	0.01859165	1390483000	21.05291701	64620	11.07627924	124349	11.73084741
2013	PIERRELS.P.A.	0	INTESASANPAOLO	0.01859543	776770000	20.47065485	71475	11.17710302	104534	11.55726766
2014	PIERRELS.P.A.	1	INTESASANPAOLO	0.01762457	636011000	20.27072642	63455	11.05808627	93057	11.44096749
2015	PIERRELS.P.A.	1	INTESASANPAOLO	0.01727723	771404000	20.46372279	54812	10.91166443	90070	11.40834242
2016	PIERRELS.P.A.	0	INTESASANPAOLO	0.014862	1020081000	20.74314787	30246	10.31711922	97105	11.48354815
2017	PIERRELS.P.A.	1	INTESASANPAOLO	0.01410158	1460111000	21.1017783	26225	10.17446843	92578	11.43580681
2018	PIERRELS.P.A.	1	INTESASANPAOLO	0.0142081	1347023000	21.02116281	34563	10.45053902	101800	11.53076538
2019	PIERRELS.P.A.	0	INTESASANPAOLO	0.01255725	851611000	20.56264041	32624	10.39280349	101838	11.53113859
2020	PIERRELS.P.A.	0	INTESASANPAOLO	0.01152886	2477057000	21.630337	36448	10.50364187	122385	11.71492709
2011	PIPEWORKSL.GIRAKIANPROFILS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.49920438	1277450000	20.96813174	37201	10.52409092	13031	9.475086413
2012	PIPEWORKSL.GIRAKIANPROFILS.A	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.36549021	1390483000	21.05291701	31211	10.34852588	11827	9.378140332
2013	PIPEWORKSL.GIRAKIANPROFILS.A	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.37621831	776770000	20.47065485	29128	10.27945519	12313	9.418410894
2014	PIPEWORKSL.GIRAKIANPROFILS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3671739	636011000	20.27072642	28035	10.24120901	14339	9.570738377
2015	PIPEWORKSL.GIRAKIANPROFILS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36730786	771404000	20.46372279	27739	10.23059464	15233	9.631219406
2016	PIPEWORKSL.GIRAKIANPROFILS.A	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.3820984	1020081000	20.74314787	28765	10.26691465	14973	9.614003858
2017	PIPEWORKSL.GIRAKIANPROFILS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.38408386	1460111000	21.1017783	25556	10.1486274	20241	9.915465529
2018	PIPEWORKSL.GIRAKIANPROFILS.A	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.36174393	1347023000	21.02116281	26296	10.17717212	20235	9.915169057
2019	PIPEWORKSL.GIRAKIANPROFILS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3170243	851611000	20.56264041	23767	10.07605334	19326	9.869206619
2020	PIPEWORKSL.GIRAKIANPROFILS.A	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.29822514	2477057000	21.630337	26100	10.16969059	16781	9.728002573
2011	VERGNETSAVSA	1	CREDITAGRICOLECORPORATEANDINVES	0.10306875	1277450000	20.96813174	73984	11.21160413	122515	11.71598875
2012	VERGNETSAVSA	1	CREDITAGRICOLECORPORATEANDINVES	0.08582987	1390483000	21.05291701	71432	11.17650123	109800	11.60641581
2013	VERGNETSAVSA	0	CREDITAGRICOLECORPORATEANDINVES	0.11910434	776770000	20.47065485	49963	10.81903801	99335	11.50625326
2014	VERGNETSAVSA	0	CREDITAGRICOLECORPORATEANDINVES	0.1328781	636011000	20.27072642	27327	10.2156305	107866	11.588645
2015	VERGNETSAVSA	0	CREDITAGRICOLECORPORATEANDINVES	0.22700144	771404000	20.46372279	28267	10.24945033	111442	11.62125956
2016	VERGNETSAVSA	0	CREDITAGRICOLECORPORATEANDINVES	0.21015708	1020081000	20.74314787	23781	10.07664222	123601	11.72481391
2017	VERGNETSAVSA	0	CREDITAGRICOLECORPORATEANDINVES	0.24012802	1460111000	21.1017783	19861	9.896513289	135902	11.81968932
2018	VERGNETSAVSA	0	CREDITAGRICOLECORPORATEANDINVES	0.25278515	1347023000	21.02116281	23640	10.07069547	155534	11.95461964
2019	VERGNETSAVSA	1	CREDITAGRICOLECORPORATEANDINVES	0.20896165	851611000	20.56264041	29153	10.2803131	173270	12.06260635
2020	VERGNETSAVSA	1	CREDITAGRICOLECORPORATEANDINVES	0.17017114	2477057000	21.630337	32703	10.3952221	200613	12.20913296
2011	BRIOSCHISVILUPPOIMMOBILIARESP	1	INTESASANPAOLO	0.01835046	1277450000	20.96813174	554804	13.22637018	131207	11.78453151
2012	BRIOSCHISVILUPPOIMMOBILIARESP	0	INTESASANPAOLO	0.01859165	1390483000	21.05291701	505971	13.13423463	124349	11.73084741
2013	BRIOSCHISVILUPPOIMMOBILIARESP	0	INTESASANPAOLO	0.01859543	776770000	20.47065485	509030	13.14026223	104534	11.55726766
2014	BRIOSCHISVILUPPOIMMOBILIARESP	1	INTESASANPAOLO	0.01762457	636011000	20.27072642	408841	12.92108161	93057	11.44096749
2015	BRIOSCHISVILUPPOIMMOBILIARESP	0	INTESASANPAOLO	0.01727723	771404000	20.46372279	379788	12.84736848	90070	11.40834242
2016	BRIOSCHISVILUPPOIMMOBILIARESP	0	INTESASANPAOLO	0.014862	1020081000	20.74314787	361373	12.79766594	97105	11.48354815
2017	BRIOSCHISVILUPPOIMMOBILIARESP	1	INTESASANPAOLO	0.01410158	1460111000	21.1017783	358296	12.78911474	92578	11.43580681
2018	BRIOSCHISVILUPPOIMMOBILIARESP	0	INTESASANPAOLO	0.0142081	1347023000	21.02116281	297336	12.60261809	101800	11.53076538
2019	BRIOSCHISVILUPPOIMMOBILIARESP	1	INTESASANPAOLO	0.01255725	851611000	20.56264041	292525	12.58630541	101838	11.53113859
2020	BRIOSCHISVILUPPOIMMOBILIARESP	1	INTESASANPAOLO	0.01152886	2477057000	21.630337	319332	12.67398659	122385	11.71492709
2011	INCITYIMMOBILIENAG	0	DEUTSCHEBANKAG	0.01051429	1277450000	20.96813174	52787	10.87402023	160605	11.98670321
2012	INCITYIMMOBILIENAG	0	DEUTSCHEBANKAG	0.01147371	1390483000	21.05291701	63581	11.06006996	153277	11.94000202
2013	INCITYIMMOBILIENAG	0	DEUTSCHEBANKAG	0.0132841	776770000	20.47065485	68182	11.12993588	143751	11.87583792
2014	INCITYIMMOBILIENAG	0	DEUTSCHEBANKAG	0.01499324	636011000	20.27072642	79933	11.28894406	143291	11.87263281
2015	INCITYIMMOBILIENAG	1	DEUTSCHEBANKAG	0.01656958	771404000	20.46372279	102967	11.54216383	149323	11.91386702
2016	INCITYIMMOBILIENAG	1	DEUTSCHEBANKAG	0.01841506	1020081000	20.74314787	115865	11.660181	155024	11.95133522
2017	INCITYIMMOBILIENAG	1	DEUTSCHEBANKAG	0.01863254	1460111000	21.1017783	144255	11.87933785	160125	11.98371004
2018	INCITYIMMOBILIENAG	1	DEUTSCHEBANKAG	0.153003	1347023000	21.02116281	169273	12.03926808	187192	12.13989011
2019	INCITYIMMOBILIENAG	1	DEUTSCHEBANKAG	0.17560497	851611000	20.56264041	186662	12.13705477	207035	12.24064314
2020	INCITYIMMOBILIENAG	0	DEUTSCHEBANKAG	0.16467272	2477057000	21.630337	182417	12.11405055	214756	12.27725778
2011	HUMANOPTICSAG	1	DEUTSCHEBANKAG	0.01051429	1277450000	20.96813174	6516	8.78201597	160605	11.98670321
2012	HUMANOPTICSAG	0	DEUTSCHEBANKAG	0.01147371	1390483000	21.05291701	6066	8.710454688	153277	11.94000202
2013	HUMANOPTICSAG	1	DEUTSCHEBANKAG	0.0132841	776770000	20.47065485	6469	8.774776816	143751	11.87583792
2014	HUMANOPTICSAG	0	DEUTSCHEBANKAG	0.01499324	636011000	20.27072642	7415	8.911260255	143291	11.87263281
2015	HUMANOPTICSAG	0	DEUTSCHEBANKAG	0.01656958	771404000	20.46372279	7429	8.913146539	149323	11.91386702
2016	HUMANOPTICSAG	1	DEUTSCHEBANKAG	0.01841506	1020081000	20.74314787	6968	8.849083519	155024	11.95133522
2017	HUMANOPTICSAG	1	DEUTSCHEBANKAG	0.01863254	1460111000	21.1017783	8059	8.994544758	160125	11.98371004
2018	HUMANOPTICSAG	1	DEUTSCHEBANKAG	0.153003	1347023000	21.02116281	9388	9.147187557	187192	12.13989011

2019	HUMANOPTICSAG	0	DEUTSCHEBANKAG	0.17560497	851611000	20.56264041	9775	9.187583385	207035	12.24064314
2020	HUMANOPTICSAG	0	DEUTSCHEBANKAG	0.16467272	2477057000	21.630337	9632	9.172846168	214756	12.27725778
2011	VIANINISPA	0	INTESASANPAOLO	0.01835046	1277450000	20.96813174	105172	11.56335238	131207	11.78453151
2012	VIANINISPA	0	INTESASANPAOLO	0.01859165	1390483000	21.05291701	109864	11.60699852	124349	11.73084741
2013	VIANINISPA	0	INTESASANPAOLO	0.01859543	776770000	20.47065485	113283	11.63764439	104534	11.55726766
2014	VIANINISPA	0	INTESASANPAOLO	0.01762457	636011000	20.27072642	116049	11.66176779	93057	11.44096749
2015	VIANINISPA	0	INTESASANPAOLO	0.01727723	771404000	20.46372279	118477	11.68247413	90070	11.40834242
2016	VIANINISPA	1	INTESASANPAOLO	0.014862	1020081000	20.74314787	474782	13.07061103	97105	11.48354815
2017	VIANINISPA	1	INTESASANPAOLO	0.01410158	1460111000	21.1017783	434442	12.98181773	92578	11.43580681
2018	VIANINISPA	0	INTESASANPAOLO	0.0142081	1347023000	21.02116281	423519	12.95635366	101800	11.53076538
2019	VIANINISPA	0	INTESASANPAOLO	0.01255725	851611000	20.56264041	302970	12.62138907	101838	11.53113859
2020	VIANINISPA	1	INTESASANPAOLO	0.01152886	2477057000	21.630337	290929	12.58083453	122385	11.71492709
2011	BANIMMONV/SA	1	INGBANKNV	0.15835991	1277450000	20.96813174	376260	12.83803567	12409	9.426177295
2012	BANIMMONV/SA	1	INGBANKNV	0.17459943	1390483000	21.05291701	403685	12.90839015	10887	9.295324696
2013	BANIMMONV/SA	0	INGBANKNV	0.17910499	776770000	20.47065485	356784	12.78488584	13283	9.494240301
2014	BANIMMONV/SA	0	INGBANKNV	0.18223707	636011000	20.27072642	339744	12.73594767	15204	9.62931383
2015	BANIMMONV/SA	0	INGBANKNV	0.31478195	771404000	20.46372279	350589	12.76736988	17130	9.748586591
2016	BANIMMONV/SA	0	INGBANKNV	0.20781971	1020081000	20.74314787	272617	12.51582316	19511	9.878733688
2017	BANIMMONV/SA	1	INGBANKNV	0.21151742	1460111000	21.1017783	188449	12.14658269	17086	9.746014694
2018	BANIMMONV/SA	0	INGBANKNV	0.21065217	1347023000	21.02116281	130876	11.78200559	20070	9.906981442
2019	BANIMMONV/SA	0	INGBANKNV	0.21304728	851611000	20.56264041	132856	11.79702111	21286	9.965804859
2020	BANIMMONV/SA	1	INGBANKNV	0.18482492	2477057000	21.630337	141562	11.86049306	21367	9.969602955
2011	RESTARTSIIQS.P.A.	1	UNICREDITSPA	0.01235034	1277450000	20.96813174	899309	13.70938197	131207	11.78453151
2012	RESTARTSIIQS.P.A.	0	UNICREDITSPA	0.0121574	1390483000	21.05291701	551351	13.22012691	124349	11.73084741
2013	RESTARTSIIQS.P.A.	0	UNICREDITSPA	0.01247691	776770000	20.47065485	522248	13.16589785	104534	11.55726766
2014	RESTARTSIIQS.P.A.	0	UNICREDITSPA	0.01222994	636011000	20.27072642	445616	13.00721287	93057	11.44096749
2015	RESTARTSIIQS.P.A.	1	UNICREDITSPA	0.01129295	771404000	20.46372279	476825	13.07490483	90070	11.40834242
2016	RESTARTSIIQS.P.A.	0	UNICREDITSPA	0.01184398	1020081000	20.74314787	502097	13.12654861	97105	11.48354815
2017	RESTARTSIIQS.P.A.	0	UNICREDITSPA	0.01316751	1460111000	21.1017783	587298	13.28328764	92578	11.43580681
2018	RESTARTSIIQS.P.A.	1	UNICREDITSPA	0.01705056	1347023000	21.02116281	30073	10.31138304	101800	11.53076538
2019	RESTARTSIIQS.P.A.	0	UNICREDITSPA	0.01604634	851611000	20.56264041	23870	10.08037772	101838	11.53113859
2020	RESTARTSIIQS.P.A.	0	UNICREDITSPA	0.01313642	2477057000	21.630337	18009	9.798626912	122385	11.71492709
2011	FULLSIXSPA	1	MEDIOBANCABANCADICREDITOFINANZI	0.00029817	1277450000	20.96813174	16821	9.730383385	131207	11.78453151
2012	FULLSIXSPA	0	MEDIOBANCABANCADICREDITOFINANZI	0.00027997	1390483000	21.05291701	14126	9.55577235	124349	11.73084741
2013	FULLSIXSPA	1	MEDIOBANCABANCADICREDITOFINANZI	0.00053255	776770000	20.47065485	14599	9.588708312	104534	11.55726766
2014	FULLSIXSPA	0	MEDIOBANCABANCADICREDITOFINANZI	0.00236643	636011000	20.27072642	17588	9.77497213	93057	11.44096749
2015	FULLSIXSPA	1	MEDIOBANCABANCADICREDITOFINANZI	0.00637013	771404000	20.46372279	29730	10.29991192	90070	11.40834242
2016	FULLSIXSPA	0	MEDIOBANCABANCADICREDITOFINANZI	0.01147959	1020081000	20.74314787	30552	10.32718543	97105	11.48354815
2017	FULLSIXSPA	0	MEDIOBANCABANCADICREDITOFINANZI	0.02124087	1460111000	21.1017783	25479	10.14560986	92578	11.43580681
2018	FULLSIXSPA	0	MEDIOBANCABANCADICREDITOFINANZI	0.02545959	1347023000	21.02116281	18992	9.851773117	101800	11.53076538
2019	FULLSIXSPA	0	MEDIOBANCABANCADICREDITOFINANZI	0.02461058	851611000	20.56264041	11992	9.39199504	101838	11.53113859
2020	FULLSIXSPA	1	MEDIOBANCABANCADICREDITOFINANZI	0.02042078	2477057000	21.630337	10815	9.288689338	122385	11.71492709
2011	OXURIONNV	0	KBCBANKNV	0.16428783	1277450000	20.96813174	129089	11.76825737	12409	9.426177295
2012	OXURIONNV	0	KBCBANKNV	0.18251204	1390483000	21.05291701	239171	12.38493406	10887	9.295324696
2013	OXURIONNV	0	KBCBANKNV	0.31289764	776770000	20.47065485	271154	12.5104422	13283	9.494240301
2014	OXURIONNV	0	KBCBANKNV	0.32509317	636011000	20.27072642	220714	12.30462302	15204	9.62931383
2015	OXURIONNV	0	KBCBANKNV	0.34829157	771404000	20.46372279	178946	12.09483936	17130	9.748586591
2016	OXURIONNV	0	KBCBANKNV	0.32605751	1020081000	20.74314787	121636	11.70878826	19511	9.878733688
2017	OXURIONNV	0	KBCBANKNV	0.29743126	1460111000	21.1017783	150437	11.92129967	17086	9.746014694
2018	OXURIONNV	0	KBCBANKNV	0.32232795	1347023000	21.02116281	114864	11.6515041	20070	9.906981442
2019	OXURIONNV	0	KBCBANKNV	0.31613543	851611000	20.56264041	65030	11.08260398	21286	9.965804859
2020	OXURIONNV	0	KBCBANKNV	0.21479264	2477057000	21.630337	34284	10.44243405	21367	9.969602955
2011	RISANAMENTOSPA	1	INTESASANPAOLO	0.01835046	1277450000	20.96813174	1983388	14.50031705	131207	11.78453151
2012	RISANAMENTOSPA	0	INTESASANPAOLO	0.01859165	1390483000	21.05291701	1900544	14.45765072	124349	11.73084741
2013	RISANAMENTOSPA	0	INTESASANPAOLO	0.01859543	776770000	20.47065485	1789269	14.39731771	104534	11.55726766
2014	RISANAMENTOSPA	0	INTESASANPAOLO	0.01762457	636011000	20.27072642	1271097	14.05539087	93057	11.44096749
2015	RISANAMENTOSPA	1	INTESASANPAOLO	0.01727723	771404000	20.46372279	1082814	13.89507377	90070	11.40834242
2016	RISANAMENTOSPA	0	INTESASANPAOLO	0.014862	1020081000	20.74314787	1011627	13.82707048	97105	11.48354815
2017	RISANAMENTOSPA	0	INTESASANPAOLO	0.01410158	1460111000	21.1017783	977006	13.79224807	92578	11.43580681
2018	RISANAMENTOSPA	1	INTESASANPAOLO	0.0142081	1347023000	21.02116281	952699	13.76705429	101800	11.53076538
2019	RISANAMENTOSPA	1	INTESASANPAOLO	0.01255725	851611000	20.56264041	729941	13.50071899	101838	11.53113859
2020	RISANAMENTOSPA	1	INTESASANPAOLO	0.01152886	2477057000	21.630337	719951	13.48693843	122385	11.71492709
2011	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.37997378	1277450000	20.96813174	31838	10.36841582	160605	11.98670321
2012	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.32714337	1390483000	21.05291701	29067	10.27735879	153277	11.94000202
2013	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.36620745	776770000	20.47065485	17705	9.781602365	143751	11.87583792
2014	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.36619514	636011000	20.27072642	14934	9.611395772	143291	11.87263281
2015	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.38947845	771404000	20.46372279	33492	10.41906188	149323	11.91386702
2016	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.4127776	1020081000	20.74314787	19055	9.855084813	155024	11.95133522
2017	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.4159004	1460111000	21.1017783	47913	10.77714215	160125	11.98371004
2018	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.40908645	1347023000	21.02116281	31256	10.34996664	187192	12.13989011
2019	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.35903839	851611000	20.56264041	52953	10.87716001	207035	12.24064314
2020	4SCAG	0	LANDESBANKHESSEN-THUERINGENGIR	0.34508307	2477057000	21.630337	42462	10.65636484	214756	12.27725778
2011	PREMIAS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.49920438	1277450000	20.96813174	217657	12.29067571	13031	9.475086413
2012	PREMIAS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36549021	1390483000	21.05291701	197793	12.19497631	11827	9.378140332
2013	PREMIAS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.37621831	776770000	20.47065485	186147	12.13429196	12313	9.418410894
2014	PREMIAS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3671739	636011000	20.27072642	168474	12.03453671	14339	9.570738377
2015	PREMIAS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.36730786	771404000	20.46372279	115835	11.65992204	15233	9.631219406
2016	PREMIAS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.3820984	1020081000	20.74314787	99213	11.50502433	14973	9.614003858
2017	PREMIAS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.38408386	1460111000	21.1017783	84833	11.3484399	20241	9.915465529
2018	PREMIAS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.36174393	1347023000	21.02116281	80253	11.29293942	20235	9.915169057

2019	PREMIAS.A.	0	ALPHASERVICESANDHOLDINGSSOCIETE	0.3170243	851611000	20.56264041	63915	11.06530935	19326	9.869206619
2020	PREMIAS.A.	1	ALPHASERVICESANDHOLDINGSSOCIETE	0.29822514	2477057000	21.630337	111181	11.61891478	16781	9.728002573
2011	AKTIENBRAUEREIKAUFBEURENAG	1	UNICREDITSPA	0.01235034	1277450000	20.96813174	10396	9.249176396	160605	11.98670321
2012	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.0121574	1390483000	21.05291701	9922	9.202509793	153277	11.94000202
2013	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.01247691	776770000	20.47065485	7389	8.907747687	143751	11.87583792
2014	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.01222994	636011000	20.27072642	8678	9.068546366	143291	11.87263281
2015	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.01129295	771404000	20.46372279	9847	9.194922119	149323	11.91386702
2016	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.01184398	1020081000	20.74314787	11834	9.378732023	155024	11.95133522
2017	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.01316751	1460111000	21.1017783	10130	9.223256597	160125	11.98371004
2018	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.01705056	1347023000	21.02116281	14697	9.59539867	187192	12.13989011
2019	AKTIENBRAUEREIKAUFBEURENAG	0	UNICREDITSPA	0.01604634	851611000	20.56264041	11388	9.340315448	207035	12.24064314
2020	AKTIENBRAUEREIKAUFBEURENAG	1	UNICREDITSPA	0.01313642	2477057000	21.630337	11528	9.352534138	214756	12.27725778
2011	CARMAT	0	EuropeanInvestmentBank	0.50385272	1277450000	20.96813174	37426	10.53012093	122515	11.71598875
2012	CARMAT	0	EuropeanInvestmentBank	0.51673483	1390483000	21.05291701	19696	9.888170848	109800	11.60641581
2013	CARMAT	0	EuropeanInvestmentBank	0.55159807	776770000	20.47065485	21984	9.998070195	99335	11.50625326
2014	CARMAT	0	EuropeanInvestmentBank	0.5354389	636011000	20.27072642	14043	9.54987933	107866	11.588645
2015	CARMAT	0	EuropeanInvestmentBank	0.53248783	771404000	20.46372279	8649	9.065198986	111442	11.62125956
2016	CARMAT	0	EuropeanInvestmentBank	0.52755845	1020081000	20.74314787	37489	10.53180284	123601	11.72481391
2017	CARMAT	0	EuropeanInvestmentBank	0.55726388	1460111000	21.1017783	69849	11.15409105	135902	11.81968932
2018	CARMAT	1	EuropeanInvestmentBank	0.551466	1347023000	21.02116281	36829	10.51404086	155534	11.95461964
2019	CARMAT	1	EuropeanInvestmentBank	0.55244746	851611000	20.56264041	64675	11.07713001	173270	12.06260635
2020	CARMAT	1	EuropeanInvestmentBank	0.55158101	2477057000	21.630337	59835	10.99934605	200613	12.20913296

A.3 Stata codes

This last section shows the codes used to perform the econometric analysis on STATA

```
//Import data
import excel "/Users/piervincenzocucinella/Desktop/Zombie Firms/General Data/Main_File.xlsx", sheet("MainSheet") firstrow clear
//The group of zombie firms is identified by names, which is read by Stata as string, it is necessary to convert it to a numeric variable
encode ZF, gen(ZF1)
//Inform Stata zombie firms are the identifying variables and year is time
xtset ZF1 year
//Create a table that summarize main characteristics of the data set's variables
summarize
//Create a two-stages least-squares probit model using the panel data set
ivprobit credit log_zftotasset log_countrysyndloans (w_bankloan = log_moneysupply log_zftotasset log_countrysyndloans), vce(cluster ZF1) first
//Perform the margins analysis
margins, dydx(*) predict(pr)
```