Public subsides and zombie lending: the Italian case during the Coronavirus spread

Eliana Sena

Thesis Advisor: Prof. Andrea Pozzi*

Einaudi Institute of Economics and Finance (EIEF) - Luiss Guido Carli

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Abstract

This paper studies the allocation across firms of government funds, disbursed through public guaranteed loans during the Coronavirus crisis. The Italian government engaged in massive efforts to support SMEs with liquidity, introducing profound and unique modifications to its public guaranteed loan scheme. I use high-quality data on guaranteed loans linked with balance sheets from incorporated firms. Results suggest that the policy is fostering zombie lending. The extensive margin entirely drives the former. This is, zombie firms are asking for more loans rather than for bigger ones. Moreover, I tested the hypothesis that partial public guarantee schemes could reduce zombie lending. I estimate Fuzzy-RD and before-after models exploiting exogenous variations introduced by the policy. I find no conclusive evidence on the connection between bank screening incentives and zombie lending. Further research including the final destination of funds, and considering an *ex-post* definition of zombie, is crucial to provide policy recommendations.

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1 Introduction

Governments often intervene to support firms during economic recessions. Their motivation includes avoiding job losses, prevent the interruption of input-output relationships hard to replace, and preclude the transmission of the recession to the financial sector in the economy [Barrot and Sauvagnat, 2016]. Generally, governments could decide to extend liquidity to firms either through direct lending or by public guarantees on private credit. Direct lending has, however, two main flaws. First, the allocation of direct lending could be based on political aspirations [Khwaja and Mian, 2005, Sapienza, 2004]. Besides, during recessions, firms need liquidity fast in order to survive [Schivardi and Guido, 2020]. Still, transaction costs and asymmetric information prevent governments from providing credit rapidly [Core and De Marco, 2021]. Hence, many governments have established public guarantee schemes as their fundamental pillar for supporting small and medium enterprises (henceforth SMEs). Nevertheless, public guarantees are not exempt from shortcomings either. Although relying on the private sector's expertise could help to speed the arrival of liquidity to firms, the important number of applications and the decrease in incentives to screen borrowers, make it difficult for the government to target the policy beneficiaries correctly. The former could end up with a substantial amount of funds flowing to weaker firms ("zombies") [Schivardi et al., 2020]. A zombie firm is defined as a low productivity firm, which systematically faces difficulties to meet its interest obligations [Rodano and Sette, 2019]. The interest in the consequences of lending to zombie firms has its origins in the Japanese crisis during the "lost decade" [Caballero et al., 2008]. Moreover, the extend of zombie lending in the economy and the consequences that it has on healthy firms is still a heated debate [Schivardi et al., 2020].

In order to analyze how resources are allocated in response to government efforts to support SMEs during recessions, this paper takes advantage of the design of the Italian public guarantee program. Like many other countries, the Italian government engaged in several modifications to the public guarantee scheme to provide SMEs with liquidity during the economic recession caused by the Coronavirus spread. First, it enormously increased the funds destined to the agency in charge of public guaranteed loans (*Fondo di Garanzia*, henceforth FG). Further, it introduced fully-guaranteed and easy-to-get loans, capped at 25,000 euro (Category I). Besides, the Decree increased the maximum percentage coverage by the government guarantee from 80% to 90% for all other loans. Moreover, for firms with sales up to 3,200,000 euro in 2019, the Decree includes the possibility of covering the missing 10% with a private guarantee (Category II). Otherwise, the bank surely shares with the government the risk for the missing part (Category III).

This paper aims to contribute to zombie lending debate, providing a first description of how resources are allocated in public guarantee systems and causal evidence on the effects of partial public guarantee on zombie lending. Thus, the paper responds to three primary objectives. First, report the main differences in loans extended to zombies versus non-zombies under public guarantee schemes. Second, study if *Decreto Liquidità* scheme is fostering zombie lending. Third, trying to disentangle between the demand and the supply-side, I exploit the discontinuity in the policy between categories and over time. The former arises as natural experiments to measure in what extent partial public guarantee affects zombie lending through changes in screening incentives.

I collected publicly available loan-level information from FG of the entire universe of firms that requested a guaranteed loan, irrespectively if the bank effectively paid out the loan. Furthermore, I obtained confidential information on the loans that were effectively disbursed. Finally, I matched the loan-level information with firm balance sheets of all incorporated firms in Italy, provided by CERVED. The final dataset comprehensively covers all the loans requested and approved by FG, containing information about their approval date, the guaranteed amount, and the type of loan. Besides, I identify which loans were further disbursed by the banks and the conditions on the credit extended: duration; interest rate. Moreover, in opposition to most papers evaluating partial public guarantees, which have information exclusively for publicly listed firms, I have information for all incorporated firms. The former allows me to study the behavior of small firms, where zombie firms are concentrated [Core and De Marco, 2021]. The inability to identify zombie firms based on 2020 information arises as to the dataset's main caveat.

In order to provide insights into the conditions of lending to zombies, I first performed a descriptive analysis. First, zombie and non-zombie firms do not face different conditions when obtaining a loan, including the loan waiting time, duration or interest rate. Nevertheless, there are differences in the type of loans that zombie firms were soliciting. At the beginning of the pandemic, zombie firms were over-proportionally asking for cheap and riskless loans in Category I, while they systematically were under-represented in the requests for bigger and more risky loans (Category II and III).

To establish if the policy is fostering zombie lending, the main empirical challenge consists of disentangling if the request for the loan is due to financial urgency, or responds to strategic behavior. To overcome this, I propose to exploit sectoral variation in the impact generated by the Coronavirus. While in sectors more negatively affected by the pandemic a massive number of requests is expected, in other sectors (henceforth, "Unaffected"), the solicitude for credit could be the outcome of strategic conduct. Hence, I estimate a cross-sectional model, identifying a sector as less negatively affected by the pandemic if by March 25 it was declared essential. Thus, it did not shut operations down between March 25 and May 15. Results suggest that the policy fosters zombie lending by reducing the gap in the amount of loan extended between zombie and non-zombie firms. While in negatively affected sectors, zombies asked on average 16,000 euros less than non-zombie firms, the difference reduces by 9,200 euro in the unaffected sectors. The extensive margin entirely drives the former. Zombie firms are over-proportionally asking for loans in unaffected sectors, but those credits are not of higher magnitude (intensive margin).

Nevertheless, results need to be taken with caution. First, I cannot claim of been estimating a causal relationship. Moreover, before making policy recommendations is crucial to analyze the destination of founds. Suppose zombie firms in unaffected sectors are investing while non-zombie firms use the credit to substitute pre-existing obligations. In that case, fostering zombie lending could be a desirable outcome of the policy. Besides, Coronavirus shock is unlikely temporary. It will imply a reallocation of resources across sectors. If zombie firms emerge from the pandemic as strong and healthy firms supported by public guarantee loans, then lending money to them could be desirable. Hence, future research considering the permanent changes in the productivity distribution is imperative.

In order to provide causal evidence of the effect of change screening incentives on zombie lending, I propose to exploit the discontinuity between Category II and III. Firms below an exogenous threshold based on 2019 firms' sales could complement the 90% public guarantee with private guarantee, while firms above the threshold could not. Theoretically, banks should be more willing to extend credit to a firm below the cut-off point rather than to an identical firm immediately above the threshold. I estimate a Fuzzy-RD model to comprehend how changes in screening incentives shapes the supply-side of partial public guarantees extended to Zombie firms. The result is non economically significant, which suggests that changing incentives to screen does not impact on zombie lending. Although this result seems to contradict the previous cross-sectional analysis, numerous motives could help to rationalize this inconsistency. First, since the loans around the discontinuity point are big, firms requesting these loans could be heavily selected. Second, a 10% increase of the risk might not be enough to compensate for the rise in screening costs. Third, firms could be engaged in agreements with banks to replace pre-existing obligations with these less risky loans.

Lastly, aiming to perform a different exercise to evaluate the change in Zombie lending due to modifications in screening incentives, I exploit the introduction of the reform. Before *Decreto Liquidità* firms could attempt for a public guarantee of 80%, hereby, the introduction of the Decree implied a decrease in incentives to screen between 10% and 20% over time. Considering firms after March 17, when the pandemic had already hit Italy, I performed a before-and-after estimation, trying to identify if there was a significant change in the probability of getting a loan approval conditional on requesting one. After the reform, I not only obtained that the probability of getting a loan approved increased by 20 pp, but it also rose even more for zombie firms, closing the pre-existing gap in the probabilities of getting a loan between zombies and non-zombies. The substantial difference with the Fuzzy-RD could be explained by the different samples of firms and banks considering in both exercises. Moreover, since firms requesting for loans before and after could be selected, this results could not be interpreted as causal evidence.

This paper contributes to the literature on zombie lending. Several papers have examined the relationship between under-capitalized banks and zombie lending [Schivardi et al., 2017, Blattner et al., 2019]. Further, many papers have focused on the consequences that Zombie lending has for healthy firms in the economy [Caballero et al., 2008, Schivardi et al., 2020]. However, fewer have studied the impact of public policies in fostering zombie lending. Little is known about how zombie lending reacts to change in incentives introduced by the government. Moreover, to the extend of my knowledge, there is no research providing causal evidence on the effect of bank screening incentives in zombie lending.

Additionally, this paper also relates to the growing literature evaluating public policies adopted to respond to the Coronavirus shock. There is abundant research on the impact of these policies on several outcomes, such as employment or consumption expenditure [Lutz et al., 2020, Chetty et al., 2020]. Moreover, several papers examine if the government efforts are flowing to firms in bigger necessity [Core and De Marco, 2021, Granja et al., 2020]. However, few paper study if the allocation of resources during the pandemic is going to weaker firms. The former also contributes to the literature on public credit guarantees since study how banks and firms react to the incentives introduced by these programs is critical to evaluate their efficiency [Schivardi et al., 2020].

This paper structures as follows. Section 2 explains the institutional framework of the public guarantee program in Italy. Section 3 describes the dataset, how I define Zombie firms, and presents summary statistics. Section 4 introduces the empirical design, while results are exhibit in Section 5. Finally, Section 6 concludes.

2 Institutional Framework

When governments aim to provide firms with liquidity, they could either provide the loans directly or rely on the private sector and operate as guarantors for the loans extended. While direct lending could lead to large defaults and adverse selection problems [Jiménez et al., 2018], partial public guarantees have become a central pillar to ensure credit provision to firms facing higher financial obstancles, namely, SMEs [Beck et al., 2008]. This mechanism is not new, becoming increasingly popular after the 2007 financial crisis [Beck et al., 2008]. In the case of Italy, *Fondo di Garanzia* is the government agency in charge of issuing public loan guarantees. It has been created in 2000 and has already extended massive support for SMEs firms during previous recessions [de Blasio et al., 2018]. Indeed, even before the Coronavirus crisis, partial guarantee schemes in Italy were already large measured against other OECD countries, covering 80% of loans up to 1,500,000 euro. Further, only in 2017, 17.5 billion euro of loans disbursed to SMEs were partially guaranteed by FG [Core and De Marco, 2021]. The important dimension of FG even before the Coronavirus crisis, combined with the profound changes introduced by the government during the pandemic, makes the Italian case a perfect set-up for analyzing the behavior of lenders during recessions, and how the public resources are being allocated. Moreover, FG is committed with huge efforts for transparency, which imply publicly available loan data at a granular level.

In response to the Coronavirus crisis, the Italian government approved on April 8, 2020 *Decreto Liquidità*. It second article determines specific measures to support SMEs through public guarantees. To begin with, it initially reinforces FG with 400 billion euro, of which 200 billion euro were dedicated to support SMEs below 500 employees. Further, to provide these firms with a quick injection of liquidity, the Italian government introduced four types of loans:

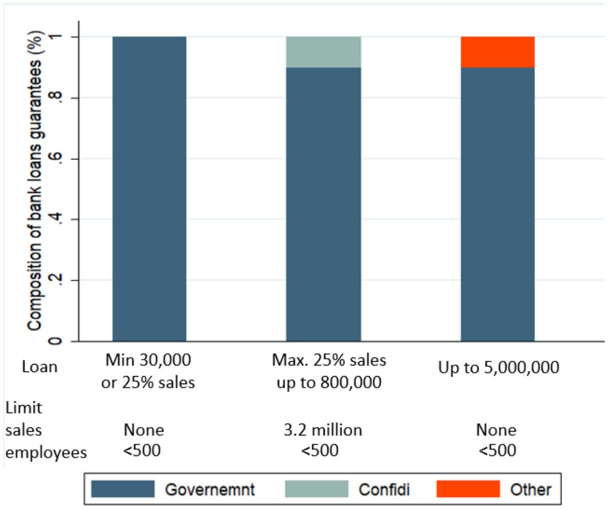
- Category I: fully guaranteed loans up to 25,000 euro (rose up to 30,000 euro in June). The requested amount could no exceed the minimum between 25% of 2019 sales and twice the labor cost in 2019. Moreover, the interest rate was capped at 2%, although the limit was periodically adjusted. The loan duration must not be longer than six years, extended to ten years in June.

- Category II: for firms with less than 3,2 million euro of sales in 2019, 90% of government guarantee for loans up to 800,000, with the possibility of covering the missing 10% with private guarantee, such as Confidi or personal funds of the firm owner. The requested amount could no exceed the minimum between 25% of 2019 sales and twice the labor cost in 2019. The duration of the loan could not exceed six years.

- Category III: 90% of government guarantee for loans up to 5,000,000 euro. The requested amount could no exceed the minimum between 25% of 2019 sales and twice the labor cost in 2019. The duration of the loan could not exceed six years.

For the first two years of the loan only interest are due, no principal payment, irrespectively of which type of loan the firm requested. Figure 1 summarize the policy scheme described above.

Figure 1: "Decreto Liquidità" Scheme



Notes: The figure provide visual intuition on the changes introduced by *Decreto Liquidità* of April 8, 2020. The blue are represents the coverage by the government. The green area represents the coverage that could be extended by a private agent. The orange area consist on the coverage by the bank.

The amount and percentage cover of the guarantee is not the only difference between the categories of loans. A critical divergence consists of the pace needed to access the guarantee. All types of loans start with an application of the firms for a bank loan, in any bank of their choice. For Category II and III, the banks require to verify the eligibility of the firm by the standards of FG [de Blasio et al., 2018]. If the firm passes the minimum standards, then FG itself performs an additional assessment concluding in approval or rejection of the guarantee. Finally, the bank itself evaluate if disbursed the loan or not. Thus, the process in Category II and III is time-consuming, costly for both the bank and the firm, and uncertain. However, to accelerate the injection of liquidity into firms, all these steps have been removed in the case of Category I. When the firms apply for a loan in the first category, they also compile a self-declaration accounting for being a business affected by the ongoing pandemic, which ensures that FG will automatically approve the loan.

3 Dataset

3.1 Source of information The first source of information consists of publicly available data on guaranteed loans, published on the website of *Fondo di Garanzia*[1]. It contains loan-level information of each requested loan that was approved by FG between March 17, 2020, and February 28, 2021, regardless of whether the loan was requested by an incorporated firm or a self-employed individual. For every loan, there is information on the date of approval by FG, the amount covered by the guarantee, the type of loan, and the total amount solicited to the bank. Further, there is also firm-level information, namely, the unique tax code of the firm, the municipality, and the sector in which the firm operates.

Additionally, I got access to confidential information containing the loans approved by the banks, and hence, effectively disbursed between March 17, 2020, and February 28, 2021. The data includes loan-level information on the date on which the loan was disbursed, the interest rate, and the duration of the loan. Besides, this source also contains the date of approval of the guarantee by FG, the total amount covered by the public agency, and the type of loan. Finally, as in the public information, each loan is complemented with firm-level information.

Thirdly, I use balance sheets information for all incorporated firm in Italy between 2017 and 2019, provided by the Firm Register (CERVED). The former entails having information of approximately 700,000 firms per year, which accounts for 70% of private sector value-added [Schivardi et al., 2017].

Finally, I hand-collected information about the status as essential or non-essential of 6-digit sectors according to the Decree of March 25.

3.2 Construction of the dataset and summary statistics The first step in constructing the dataset is the union through the unique tax code between FG public information and firms' balance sheets. It allows identifying which of the firms that requested a loan are incorporated firms. Additionally, it establishes the take-up rate of the policy since it distinguishes the firms that did not solicit a loan.

[1] https://www.fondidigaranzia.it/amministrazione-trasparente/

Secondly, I merge the public and the confidential information provided by FG, which permits identifying whether the loans approved by FG are then approved or rejected by the banks. However, the confidential information does not have a unique tax code identifier. To overcome this, I perform the match based on loan and firm characteristics.[2]

Hence, after restricting the sample to incorporated firms, I obtained firm-loan information establishing for each firm if they requested a loan, whether the loan was disbursed, and the conditions under which the loan was extended. Finally, for each firm, I include the full information comprise in the balance sheet, independently if the firm requested a loan. While the majority of papers studying the effects of public guarantees rely on information for publicly listed firms [Core and De Marco, 2021], one of the main advantages of my dataset is to possess data for all incorporated firms. The above-mentioned allows me to get granular firm-loan information including very small firms.

Of the entire universe of incorporated firms, 47% requested a guaranteed loan, which implies an important take-up rate of the policy. Table 1 presents the summary statistics of the FG-CERVED sample. The first Column shows the total number of loans requested by Category. The second Column presents how many of those loans were solicited by incorporated firms. Finally, Column three contains the loans requested for incorporated firms that were effectively disbursed.

Table 1: Final sample - descriptive statistics

	Loan request	Loan req. by incorporated firms	Disbursed loans
Category I	1,091,737	231,917	169,845
Category II - III	332,124	234,968	173,471
Other	49,708	9,665	6,304

Approximately 74% of the guaranteed loans requested were for Category I, which corresponds to the smallest credit with 100% of coverage from the government. However, only 21% of these petitions were made by incorporated firms. On the contrary, although Category

[2]The variables contained in the merge are: municipality of the firm, sector, type of loan, amount of the loan approved by the FG, total amount request by the firm, date of approval by FG.

II and III requests are one-third of the total requests for Category I, 70% of those requests were made by incorporated firms. Finally, 26% of the requested loans by incorporated firms were not disbursed in Category II and III[3].

3.3 What is a zombie firm?

The final step in the construction of the database is to operationalize the definition of zombie. Zombie firms are defined as low profitability firms, with difficulties in meeting their interest obligations [Rodano and Sette, 2019] or that are receiving subsidize credit [Caballero et al., 2008]. The concern for zombie lending was first introduced to explain the length and depth of the Japanese economic crisis during the 90's [Caballero et al., 2008]. However, the interest in the impact of zombie firms in the economy has steady grown since the 2007 Global Financial Crisis.

Although several articles measure the incidence and consequences of zombie firms in the economy [Caballero et al., 2008, Schivardi et al., 2017, McGowan et al., 2017a,b], there is not a consensus in the literature regarding how to empirically define a zombie firm. In a seminal paper, [Caballero et al., 2008] classify a firm as a zombie if it received subsidize credit. More generally, a widely extended definition is the one adopted by the OECD [McGowan et al., 2017a], in which a firm is a zombie if its ratio of operating profits to interest payments is less than one for three consecutive years (approximated as EBIT/interest payment < 1), and the firm is at least ten years old.

Classifying firms as zombies based on subsidize credit extension in 2020 is likely misleading. The Italian Government launched several measures intending to facilitate the access to subsidize credit even for firms that were healthy before the crisis [Schivardi et al., 2020]. Furthermore, healthy and productive firms could face high interest payments and low returns due to economic difficulties caused by the ongoing pandemic. Suppose those firms survive due to the injection of liquidity through a guaranteed loan, returning to their previous levels of productivity after the crisis. Then, lending to these firms could be considered as a positive outcome of the policy, even if in 2020 they could be defined as zombies.

Hence, to distinguish the effect of a temporary shock from a structural condition, I

[3] In the case of Category II-III, the loans that did not match in the third Column were not disbursed. However, in Category I, the loans that do not match are probably due to the incapacity of uniquely identify the firm in the public and confidential loan information. From anecdotal evidence, the disbursement rate among loans requested in Category I was virtually 100%.

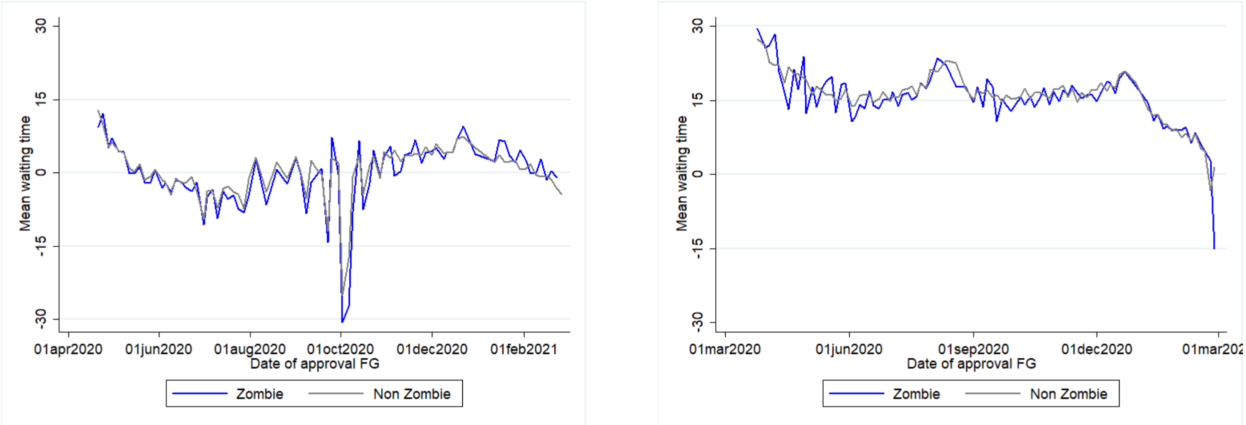
propose classifying zombies using the balance sheet information of years previous to the pandemic. Considering that zombie condition is rather stable [Schivardi et al., 2020], identifying zombie status using precedent information is accurate as long as the Coronavirus shock does not alter the relative productivity of a firm within economic sectors. Therefore, adjusting the OECD definition to the available data, I classify a firm as a zombie if the rate of EBIT to interest payments is less than 1 for 2019 and 2018, and they survive for the entire three years of my sample. Following this approach, 11% of incorporated firms in 2019 were zombies. On average, while zombie firms have twice the leverage than Non-zombie firms, their sales represent 88% of the sales of Non-zombie firms, suggesting that zombies are smaller firms.

An important limitation of my strategy is disregarding a crucial aspect of the Coronavirus crisis. As stated by [Barrero et al., 2020], the changes introduced by the ongoing pandemic are not transitory shocks. Instead, the current recession will plausibly generate permanent reallocation of resources across sectors. Further, firms that were before marked as of low productivity could emerge from the crisis as strong and healthy firms. Therefore, the approach proposed in this paper needs to be taken as a first approximation to analyze the allocation of public resources during the economic slowdown. Nevertheless, before jump to conclusions about the efficiency of the policy, it is imperative a more careful ex-post definition of zombies firms.

3.4 Zombie lending: descriptive analysis

In order to get some insights on the differences in loan allocation between zombies and non-zombie, this section contains the results of a descriptive analysis. The preliminary inquiry regarding loans extended to zombies is if there could exist heterogeneity in the conditions at which zombie and non-zombie firms are accessing the guarantee. To answer this, Figure 2 depicts the daily average waiting time of disbursement of the loan, define as the number of days between the approval of the guarantee by FG and the actual day on which the bank payout the loan. Panel (a) shows the waiting time for Category I, while Panel (b) does it for Category II and III. In both cases, the blue line corresponds to the waiting time that zombie firms faced and the grey line the one of non-zombie firms.

Figure 2: Waiting time between the approval date of FG and the disbursement of the loan: zombie firms by category



(a) Category I

(b) Category II - III

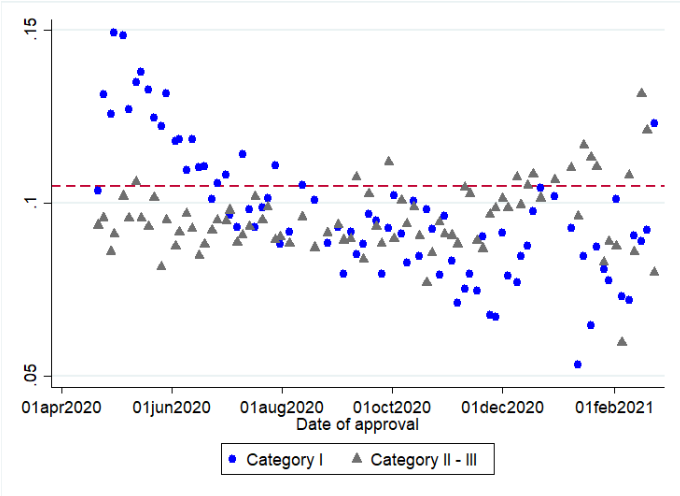
Notes: The figure depicts the daily average waiting time of disbursement of the loan, define as the number of days between the approval of the guarantee by FG and the actual day on which the bank payout the loan. Panel (a) shows the waiting time for Category I, while Panel (b) does it for Category II and III. In both cases, the blue line corresponds to the waiting time that zombie firms faced and the grey line the one of non-zombie firms.

As expected, loans in the first category faced lower waiting times. At the beginning of the program, the average waiting time for Category I loans was ten days. It rapidly goes to negative values, implying that the bank disbursed the loan even before knowing the approval decision of FG. The former supports that not only full guarantee, but also a reduction in the bureaucratic steps to access the loan, as described in Section 2, could be essential to accelerate the arrival of liquidity to firms. On the other hand, loans in Category II and III, riskier and more costly for banks, faced higher waiting times, stabilizing around 15 days after one month the policy begun to be implemented.

Interestingly, there are no differences in the waiting time between zombie and non-zombie firms. Moreover, the waiting time of both zombie and non-zombie follows the same path for all types of loans. Appendix A shows that there are no differences between zombie and non-zombie, neither in the duration of the loan, in the interest rate, or in the waiting time of approval. The waiting time of approval is defined as the number of days passed between the moment in which the request is made to FG, and the day in which FG approved the guarantee. Hence, the policy is not encouraging contractual differences between zombie and non-zombie firms.

However, there is heterogeneity between zombie and non-zombie firms when considering the type of loans requested, and its dynamics over time. Figure 3 depicts the daily proportion of loans disbursed that were asked for zombies.

Figure 3: Quantity of disbursed loan: proportion zombie firms by loan category



Notes: The figure depicts the daily proportion of loans disbursed that were asked for zombies.The blue dot corresponds to the loans in Category I. The grey triangles corresponds to the loans in Category II. The red horizontal line corresponds to the proportion of zombie in the population.

The blue dot corresponds to the loans in Category I. At the beginning of the pandemic, the daily proportion of loans that were disbursed to zombies exceeded their proportion in the firm population (11%, red line). Overall, the former suggests that zombie firms over-proportionally asked for cheap and easy-to-access loans at the beginning of the pandemic. Nevertheless, from the previous figure it is not possible to infer if this fact its the result of an over-concentration of zombie firms in sectors negatively affected by the pandemic, or, on the contrary, is due to a strategic behavior from zombies, trying to take profit of a free-loan policy. As time goes by, the trend reverses, and non-zombie firms' requests for Category I loans rise until be above their proportion in the firm population.

On the other side, zombie firms tend to be under-represented in the requests for loans in Category II and III (represented by the grey triangles) until the beginning of 2021. Overall, zombie firms are selecting themselves in less risky, cheaper, and smaller loans than non-zombie firms.

4 Empirical design

4.1 Zombie lending and government guaranteed loans To measure the extent to which the public guarantee policy fosters zombie lending, the first empirical challenge consists of disentangling firms' economic struggling from strategic behavior. The Coronavirus implied an exogenous demand shock to firms. Thus, if zombies are heavily concentrated in sectors negatively affected by the pandemic, results mechanically would suggest an over-proportional request of loans by zombie firms. However, it would not be motivated by the willingness of take profits from a free-loan policy, but by the need for urgent liquidity to survive. Moreover, suppose the government's objective is to save the firms *no matter what*. In that case, lending to zombie firms in financial difficulties induced by the recession is not a harmful result of the policy.

In order to overcome this problem, and considering that the Coronavirus shock did not distribute uniformly across sectors, I propose to exploit the sectoral divergences of the impact of the pandemic. By way of illustration, while air transportation was the sector more negatively affected by the pandemic, losing 46% of its sales with respect to 2019, the retail sector increases its sales by 32% in 2020 [Schivardi and Guido, 2020]. The main hypothesis is that, while in the sectors negatively affected by the pandemic most firms are asking for loans, with the ultimate objective of surviving, in the less affected sectors the behavior of the firms could be more strategic. In those sectors, it is particularly interesting to see if zombie firms are over-proportionally requesting loans. Hence, I propose the following regression framework:

$$Loan_i = \beta_0 + \beta_1 \text{Unaffected sector}_i + \beta_2 Zombie_i \tag{1}$$

$$+ \beta_3 \text{Unaffected sector}_i * Zombie_i + \gamma X_i + \epsilon_i \tag{2}$$

Where the dependent variable $Loan_i$ is the total amount of guarantee extended to firm i after April 24, 2020[4]. Unaffected sector is a dummy equal to one if the 6-digit sector

[4] Although *Decreto Liquidità* was approved on April 8, it did not come into force until April 24, 2020.

was declared essential in the Decree of March 25, 2020, thus, remained open between the issuance of the Decree and May 15, 2020. Following Core and De Marco [2021] and Schivardi and Guido [2020], firms declared essential experienced less negative shocks in their demand than firms declared non-essential. Consequently, this variable acts like a proxy identifying sectors less negatively affected by the pandemic[5] (henceforth, unaffected). The variable $Zombie_i$ corresponds to a dummy equal to one if the firm was a zombie in 2019. Vector $\mathbf{X}_i$ is a vector of firm controls. Following [Core and De Marco, 2021]: log of total assets; cash and liquid assets over total assets; leverage; EBITDA over assets. Additionally, it also includes 3-digit sector classification and province fix effects. In this regression framework, β_1 indicates the difference between unaffected sectors and affected sectors in the amount of loan distributed to non-zombie firms ($\beta_1 = Loan_{NZ/UN} - Loan_{NZ/AFF}$). On the other hand, β_2 depicts the divergence in the access to loans for zombie firms with respect to non-zombie firms in affected sectors ($\beta_2 = Loan_{Z/AFF} - Loan_{NZ/AFF}$).

To test the main hypothesis, the coefficient of interest is β_3, which corresponds to the interaction between the zombie dummy and the unaffected sector dummy. It indicates the relative difference in access to loans in unaffected and affected sector, for zombie vs. non-zombie firms ($\beta_3 = (Loan_{Z/UN} - Loan_{NZ/UN}) - (Loan_{Z/AFF} - Loan_{NZ/AFF})$). $\beta_3 > 0$ connote suggestive evidence of a fostering in zombie lending induced by the policy. Additionally, if it is true that firms in affected sectors are making use of the policy more aggressively than firms in Non-affected sectors, then $\beta_1 + \beta_3 < 0$[6]. Finally, in order to test which channel is guiding the results, $Loan_i$ is replaced by a dummy taking value one if the firm i received a loan (extensive margin) and by the total amount of guarantee extended to the firm i among those firms who obtained credit (intensive margin).

Even though the former regression could return suggestive evidence that the policy fosters zombie lending, the results can not be interpreted causally. Although being declared essential on March 25 generates an exogenous negative shock in demand, the variable zombie could be

[5]Firms concentrated in sectors declared non-essential were close between March 25 and May 15, which mechanically decrease their sales. Additionally, in subsequent decrees, sectors with higher restrictions to operate coincide with the sectors declared non-essential on March 25. On the other hand, sectors declared essential were less concentrated in activities that could be affected by reducing the population's mobility. Appendix C shows the correlation between been declared essential and the drop in sales in 2020 predicted by CERVED sectoral experts.

[6]Figure 11 of the Appendix visually describes the intuition behind this hypothesis

correlated with some unobservable component in the error term, biasing the results. Even more, before making claims about the efficiency of the policy, it is crucial to consider that the Coronavirus shock is not a transitory one. As mentioned in Section 3.3, a reallocation of resources across sectors is likely to occur. Suppose zombie firms operating in sectors not declared essential are specializing in an industry that benefits from the shock that the economy is experiencing. In that case, lending money to these firms, opening their opportunities to invest and growth, could be a very desirable outcome of the policy.

4.2 Bank screening and zombie lending

4.2.1 Regression Discontinuity Before making policy recommendations regarding public guarantees, it is crucial to understand if the policy generates a shift in the behavior from the demand-side (the firms), the supply-side (the banks), or both of them. Of course, disentangling these effects is usually challenging. There is little causal evidence on the extent in which partial public guarantee systems could decrease zombie lending through an increase in banks incentives to screen. In order to provide causal evidence on the effects that reducing risk for banks has in zombie lending, I propose to exploit the discontinuity between Category II and Category III. As mentioned in Section 2, the Decree established that for those firms with sales up to 3,200,000 euro in 2019, a private guarantee could be added on top of the 90% public guarantee, namely Confidi or personal funds. The former implies that these loans are virtually 100% covered for the bank, involving zero risks. On the other hand, for firms immediately above the threshold the bank surely has to carry with the 10% of the losses if the firm does not face its debt obligations. Hence, sharing some risk with the government. From a theoretical perspective, the former should diminish the risk of moral hazard and increase banks' incentives to screen. As a result, it is expected that if a zombie firm is immediately below the threshold, the probability that a bank is willing to lend to it is higher than if the same firm is immediately above the threshold. To test this hypothesis, I estimate a Fuzzy-RD equation considering only zombie firms around the threshold[7]

[7]As firms in Category II do not have to mandatory complement the public guarantee with a private one, there is no perfect compliance with the policy. Hence, I propose a two-stage estimation for the Regression Discontinuity exercise.

$$Loan_i = f(sales_i, 2019) + \rho \hat{Treatment_i} + X_i\gamma + \epsilon_i \tag{3}$$

Where $loan_i$ is the amount of loan obtained by zombie firm i. $f(sales)$ is a polynomial fitting for the discontinuity variable, in this case, sales of 2019. $\hat{treatment_i}$ its the second-stage instrumented treatment dummy, this is, below or above the threshold. Vector X_i is identical to the one in equation 1. The coefficient of interest is ρ which indicates a discontinuity in zombie lending between sides of the threshold.

My identification strategy exploits the discontinuity in the policy scheme and relies on the exogeneity of the threshold. Hence, the main assumption is that firms do not manipulate the discontinuity variable (sales of 2019) to be on the left side of the threshold. The former assumption seems plausible as most firms forwarded balance sheets before April, the moment in which the Decree was announced. Moreover, the Coronavirus shock was unexpected, avoiding anticipation effects from the firms. Finally, the 3,200,000 euro threshold does not coincide with the threshold of any other policy, such as tax declaration. Therefore, *a priori* firms did not have incentives to manipulate their sales below the cut-off point. Finally, distribution of firms around the sales threshold is smooth.

Before and after An additional approach to estimate the effects of changing the incentives to screen in zombie lending consists of analyzing banks' responses to the introduction of *Decreto Liquidità*[8]. Hence, I propose to exploit the discontinuity overtime on the percentage covered by the public guarantee. While before April 8 the public guarantee covered 80% of the loan, after the Decree the amount was raised to 100% for small loans (Category I) or to 90% with the possibility of adding a 10% of private guarantee (Category II). Intuitively, banks who received a request for a loan before *Decreto Liquidita* had higher incentives to turn down the loan rather than when the guarantee coverage became higher. The former is probably a mechanical effect of the Decree and would indicate a success in providing fast liquidity to firms. However, the decrease in incentives to screening could over-proportionally

[8]The first Decree launched to assist firms as a response to the Coronavirus was *Decreto Cura Italia*, on March 17, 2020. However, the former included only modifications to the conditions of loans that were already disbursed.

raise the lending to zombies. In order to test this, I perform a before-after exercise, aiming to retrieve the changes in the probability for zombies of getting a loan approved, conditionally on having request a loan. The regression framework to estimate is as follows:

$$Loan_{it} = \alpha_0 + \alpha_1 After_t + \alpha_2 Zombie_i + \alpha_3 Zombie_i * After_t + \gamma * X_i + \epsilon_{it} \tag{4}$$

Where $Loan_{it}$ is a dummy that takes value equal to 1 if the loan requested by firm i in period t was approved, where t could take two values: $t = 1$ before April 24 and $t = 2$ after April 24[9]. $Zombie_i$ is a dummy taking value 1 if the firm i is a zombie in 2019; $After_t$ is a dummy taking value 1 if the date of approval of the loan is after April 24, 2020. $\mathbf{X}_i$ is a vector of controls identical to the one in equation 1. Coefficient α_1 expresses the difference in the probability of getting a loan approved for non-zombie firms before and after the reform ($\alpha_1 = Loan_{NZ/AFTER} - Loan_{NZ/BEFORE}$). Further, α_2 represents the difference in the probability of loan approval for zombie with respect to non-zombie firms, before that the reform took place ($\alpha_2 = Loan_{Z/BEFORE} - Loan_{NZ/AFTER}$). Finally, the coefficient of interest is α_3. It represents the relative difference in the probability of getting a loan approved before and after the reform, for zombies vs non-zombie firms ($\alpha_3 = (Loan_{Z/AFTER} - Loan_{NZ/AFTER}) - (Loan_{Z/BEFORE} - Loan_{NZ/BEFORE})$). If $\alpha_3 > 0$, then zombies are increasing the probability to access a loan more than the average firm in the economy. Interestingly, the exercise proposed in Section 4.2.1 analyzes the effects of *increase* the incentives to screen in zombie lending, considering the difference in *loan size*. On the other hand, the before-after exercise examines the consequences of *decrease* the incentives to screen in zombie lending, varying *over time*.

Remarkably, although α_3 provides suggestive evidence of an increase in zombie lending when the incentives to screen decrease, the results cannot be taken with a causal approach. First, firms before and after the threshold could substantially differ. Although also firms in the "before" period are affected by the pandemic, firms requesting a loan more than a month

[9] Although the Decree was approved on April 8, it did not come into force until April 24. In order to get comparability of periods, I consider loans approved up to May 31, which gives a window of 1 month and 1 week both before and after.

after the Coronavirus outbreak the economy might be firms that are internalizing the shock differently. For instance, at the beginning of the Coronavirus, it might be that only firms in desperate situations were asking for loans ("before"). However, as the pandemic goes by, more firms start to face liquidity constraint [Schivardi and Guido, 2020] and request for loans ("after"). If firms in the "after" group are stronger firms, even in the absence of the policy they would have greater probabilities of getting a loan. Then, part of the effect captured by α_1 is mechanical, independently of the change in screening incentives. The former is particularly relevant if zombie firms behave differently from non-zombie firms before and after the Decree. If that is the case, $\alpha_3 > 0$ could be entirely driven by the fact that the "best" zombie firms are asking for loans after the Decree, while the opposite is true for the case of non-zombie firms. Hence, α_3 being completely orthogonal to the change in banks' incentives to screen.

Mitigating some of the concerns discussed above, firms asking for loans before and after April 24 do not significantly differ in sales, leverage, assets or economic sector. Moreover, more than 1000 firms that requested a loan "before" and were rejected solicited a loan again between April 24 and May 31. Of those, 71% obtained the credit in their second attempt. Banks approving loans for the exact same firm after the introduction of the policy seems to indicate that, at least to some extent, modification in the screening incentives could change the outcome of the loan. Despite the last remarks, results need to be taken with caution.

5 Results

5.1 Zombie lending and government guaranteed loans The results of estimating equation 1 are presented in Table 2. In Column (1), the dependent variable is the total amount guaranteed by FG. First, β_1 is positive and significantly different from zero, meaning that non-zombie firms in unaffected sectors obtained approximately 35,000 euros more of guaranteed loan than non-zombie firms in affected sectors. Coefficient β_2 is negative and statistically significant, which implies that zombie firms obtained approximately 16,000 euros less of guaranteed loan than non-zombie firms in affected sectors. Moreover, the coefficient of interest β_3 is positive and significantly different from zero. The former is suggestive evidence that the policy could be fostering zombie lending. In sectors less affected by the pandemic, in which it is expected that fewer loans are requested to keep the firm afloat, zombie firms are over-proportionally asking for loans. Furthermore, this effect is a consequence of the reduction in the loan amount gap between zombie and non-zombie firms. While in affected sectors zombies asked, on average, 16,000 euros less than non-zombie firms, the difference is reduced by 9,200 euro in the unaffected sectors. Finally, in opposition to the hypothesis exposed in Section 4.1, firms in unaffected sectors are obtaining a larger amount of credit than firms in affected sectors. The above-mentioned could be pointing to a general strategic behavior from firms in less affected sectors, not only by zombie firms.

Table 2: Zombie lending and government guaranteed loans: cross-section

	Total	Extensive Margin				Intensive Margin					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Total	Total	Apr-Jun	Jul-Sep	Oct-Feb	Total	Apr-Jun	Jul-Sep	Oct-Feb	Cat. I	Cat. II
Interaction	9193.4***	0.0502***	0.0321***	0.0349***	0.0409***	-2319.1	1154.3	-1307.0	-17927.5**	-33.10	-9702.0
	(2090.6)	(0.00347)	(0.00367)	(0.00348)	(0.00336)	(3577.1)	(3338.1)	(7628.6)	(9008.4)	(84.01)	(8437.6)
Unaffected sector	34619.5***	-0.0627***	-0.0744***	-0.0474***	-0.0270***	33570.4***	37354.0**	28957.3***	26891.1**	578.4***	31326.5***
	(3626.7)	(0.00449)	(0.00497)	(0.00490)	(0.00480)	(9662.5)	(17379.6)	(10583.1)	(11513.8)	(120.9)	(9290.5)
Zombie	-15974.0***	-0.0611***	-0.0156***	-0.0621***	-0.0704***	-11718.1**	-20887.3***	-19564.2***	15186.6	-129.4	-6478.4
	(2089.4)	(0.00364)	(0.00394)	(0.00376)	(0.00359)	(4963.0)	(4488.8)	(7329.8)	(9384.4)	(85.03)	(8274.9)
Observations	819959	819969	594871	541525	521947	400772	175677	122335	102760	231900	168872
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the loan amount disbursed to firm i. Unaffected $sector_i$ consist on a dummy taking value 1 if the firm operates in a sector declared essential in the Decree of March 25, 2020. $Zombie_i$ is a dummy taking value 1 if the firm is classify as zombie in 2019. The coefficient of interest is $interaction = Unafected\ sector_i * Zombie_i$. Following [Core and De Marco, 2021] the control variables are: log of total assets; cash and liquid assets over total assets; leverage; EBITDA over assets. Additionally, I also included 3-digit sector classification and province fix effects. In Column (1) the dependent variable is the total amount disbursed to firm i. Column (2) through (5) display the results of the extensive margin, thus, the dependent variable is a dummy taking value 1 if the firm received a loan. Column (3) to (5) presents the dynamic effects. Column (6) to (11) show the results of the intensive margin, thus, the dependent variable is the total amount of loan disbursed among the firms who got a loan. Column (7) to (9) presents dynamic effects. Column (10) and (11) depicts the regression by category of loan.

Columns (2) through (6) displayed the results of the analysis in the extensive margin, this is, estimating equation 1 considering as dependent variable a dummy equal to 1 if the firm obtained a guarantee in the period of interest. In line with the main hypothesis, $\beta_1 + \beta_3$ is negative, which implies that firms in non affected sectors are asking for fewer loans than firms in the affected ones. Nonetheless, coefficient β_3 is positive, indicating that the probability of getting a loan for a zombie vs. a non-zombie firm is 5 pp. higher in unaffected than affected sectors. Once more, everything is driven by a reduction in the gap of loan requests between zombie and non-zombie firms in unaffected sectors. While in an affected sector, the probability of getting a loan is 6.1 pp. smaller for zombie firms (β_2), the gap is reduced by 5 pp. when we moved to an unaffected sector. Columns (3) to (6) examine the dynamics effect of the pandemic. Interestingly, at the beginning of the pandemic (Column (3)), non-zombie firms in unaffected sectors asked relatively for fewer loans with respect to non-zombie firms in affected sector than in the average. Moreover, the sum of β_1 and β_3 is higher in absolute value than at the average, which reflects the idea that at the beginning of the pandemic were the firms in more desperate financial needs the ones who asked for loans. This trend reverses up to the point that in October-February, the firms in unaffected sectors have higher probabilities of getting a loan.

However, in all cases, the interaction coefficient is positive and significant, suggesting that one of the reasons for the result found in Column (1) is a higher amount of requests for loans by zombie firms in less affected sectors. Further, at the beginning of the pandemic coefficient β_3 exceed on absolute value β_2, suggesting that not only the gap between zombie and non-zombie was closed in unaffected sectors, but that zombie firms asked, on average, for more loans than non-zombie firms.

Finally, Columns (7) to (11) examined the intensive margin, thus, estimating equation 1 using as dependent variable the total amount of guarantee among the firms that obtained a loan. In Column (7), the coefficient of interest β_3 is not economically significant. The former implies that zombies are not over-proportionally asking for bigger loans in non affected sectors than in affected sectors. Moreover, β_1 is again positive, which, together with a non-significant interaction, indicates that firms in unaffected sectors are asking for bigger loans. Finally, β_2 indicates that, on average, zombie firms asked for loans 21,000 euro smaller than non-zombie firms, which, due to β_3 insignificant, it is true irrespectively of the type of sector in which the firm operates. The former is coherent with the discussion in Section 3.4: zombie firms are over-proportionally concentrated in Category I requests, this is, in smaller loans. The results obtained in the intensive margin are constant over time, except at the end of the period. From October to February, the amount of loans asked by zombie and non-zombie firms in affected sectors have no significant difference. Even more, in unaffected sectors, zombie firms asked relatively for smaller loans than non-zombie firms, compared with the same firms in affected sectors. Columns (10) and (11) split the analysis according to the type of loan asked by the firm. As before, non-zombie firms asked for bigger loans in unaffected sectors. For neither of the loans coefficient β_3 is significant.

Overall, firms in unaffected sectors are obtaining a larger amount of cash than firms in affected sectors. The former is entirely driven by the intensive margin. Hence, firms in unaffected sectors are asking for fewer loans but larger amounts. Firms in higher financial needs, those in affected sectors, may be willing to ask for smaller loans as they are faster, leaving bigger loans with higher risk and waiting time to firms that do not need an urgent inflow of liquidity to survive. On the other hand, while the results suggest a fostering in zombie lending, it is entirely guided by the extensive margin. Thus, zombie firms in less affected sectors are probably selecting themselves into the safer and quicker loans. Part of this result is mechanical as zombie firms are smaller. However, it could also imply that zombie firms even in less affected sectors are in bigger necessity of cash than non-zombie firms. Furthermore, zombie firms could potentially anticipate that they would not pass the requirement needed for bigger loans.

Finally, as mentioned in Section 4.1, the previous results should not be interpreted in a causal framework. Moreover, even if the findings suggest a fostering in zombie lending, a claim regarding policy evaluation needs further information. First, shocks as the one of Coronavirus are likely permanent. Hence, firms before considered as zombies might become very productive under the new economic environment. If zombies are dedicating the money for investment and development, then an over-proportionally request of loans by zombies could be a desirable outcome of the policy. Second, knowing the final use of the funds is crucial to make judgments about the policy's success. While loans could be used to cover liquidity constraints or to invest, they can also be used to substitute pre-existent debt. If non-zombie firms are substituting credit while zombie firms are not, then fostering zombie lending is not necessarily negative.

5.2 Bank screening and zombie lending

5.2.1 Regression Discontinuity

To study if changes in the incentives to screen generates a shutting in zombie lending, I use an RD design, exploiting the difference in guarantee coverage around a exogenous threshold between Category II and III[10]. The results of estimate equation 3 are display in Table 3. Column (1) reports the results of a linear fit, where the treatment effect is non statistically different from zero. The same occurs when the fit is made through a quadratic polynomial (Column (2)) and separated by date (Column (3) to (5))

Table 3: Bank screening and zombie lending: Fuzzy-RD

	(1) Linear	(2) Polynomial	(3) Apr-Jun	(4) Jul-Sep	(5) Oct-Feb
Treatment	20970.7	43951.7	-10200.7	-22635.9	34794.2
	(24105.7)	(51002.5)	(45561.2)	(40959.1)	(35591.6)
Observations	1931	1931	2457	2937	3119
Region	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Polynomial	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the loan amount disbursed to firm i. The coefficient of interest, *Treatment*, is the instrumented treatment dummy, taking value one above the threshold. The regression includes a polynomial fit of the discontinuity variable (sales). Following [Core and De Marco, 2021] the control variables are: log of total assets; cash and liquid assets over total assets; leverage; EBITDA over assets. Additionally, I also included 3-digit sector classification and province fix effects. Column (1) fits a linear polynomial. Column (2) through (5) fits a quadratic polynomial. Column (3) to (5) present dynamic effects.

At first sight, results in Table 3 contradict standard economic theory on bank screening. Moreover, they seem to disclaim the results presented in Section 5.1. There are, however, several reasons that help to rationalize these findings. Firstly, the mechanism design might not be incentive-compatible to fostering banks to start screening firms above the threshold. Screening is likely a costly process for banks not compensated for the 10% risk increase. Secondly, the Fuzzy-RD design is local, while the results presented in Section 5.1 are considering the average of the population. The amount of the loans around the threshold are

[10]Figure 12 of the Appendix visually shows the loan discontinuity around the threshold.

above the media of loans extended. Additionally, zombie firms around the threshold have bigger sales and leverage than firms in the rest of the population. Hence, this result could be driven by the fact that banks have different screening policies for these firms than for the rest of the firm population.

Moreover, CONFIDI could also perform some screening before giving their guarantee. If the former is an extensive practice, then firms in Category II with a CONFIDI guarantee are likely similar to those who got a loan approved by the bank above the threshold. Finally, a crucial point to understand the strategic behavior of the banks is to carefully examine the previous relationships with the firms to which they are lending. If firms asking for loans in Category III were already debtors of that bank, a firm-bank agreement could exist though which part of the loan is used to cover previous debt. This movement would substitute risky debt with a debt with a maximum loss not exceeding 10% of the loan total. In line with this hypothesis, Core and De Marco [2021] find that pre-existing lending relationships and local banking markets determine the allocation of guaranteed lending. Moreover, Appendix E.2 shows that loans in Category II and III are disbursed solely by small banks[11], to which firms could have closer relationships.

5.2.2 Before-after Intending to study the effect of change in the supply-side incentives in zombie lending, I also propose a before and after exercise exploiting the changes over time in the incentives to screen. Table 4 presents the results of estimating equation 4. In Column (1), the dependent variable consists of a dummy taking value 1 if a requested loan got approved and 0 otherwise. First, as expected, α_1 is positive and economically significant; a non-zombie firm that requested a loan after the introduction of the Decree increased its probability of getting the loan approved by 20 percentage points. α_2 is negative and significant, which implies that the probability that a loan requested by a zombie firm was approved before the Decree was 1.3 pp smaller than for Non-zombie firms. More interestingly, α_3 is positive and significant, implying that zombie firms are over-proportionally getting loans approved after the reform. Overall, it seems to suggest that decreasing incentives to screen is fostering zombie lending.

[11]Big banks are defined as those belonging to the top 10 of banks who disbursed the biggest amount of loans.

Table 4: BANK SCREENING AND ZOMBIE LENDING: BEFORE AND AFTER

	Probability of get a loan			Amount loan
	(1)	(2)	(3)	(4)
	Loan	Loan	Loan	Amount
Interaction	0.0159**	0.00979	0.0244**	8349.7
	(0.00778)	(0.0212)	(0.00989)	(8180.9)
After	0.199***	0.102***	0.253***	-22789.0***
	(0.00227)	(0.00612)	(0.00289)	(2383.2)
Zombie	-0.0128*	-0.0237	-0.0215**	-21783.3***
	(0.00764)	(0.0184)	(0.00979)	(8030.0)
Observations	108318	18711	105427	108221
Sector	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Among those who requested a loan, the dependent variable is a variable taking value 1 if the loan was approved. $After_i$ is a dummy variable taking value 1 after the come into force of the Decree. $Zombie_i$ is a dummy taking value 1 if the firm is classify as zombie in 2019. The coefficient of interest, *interaction*, is the interaction between the two dummies. Following [Core and De Marco, 2021] the control variables are: log of total assets; cash and liquid assets over total assets; leverage; EBITDA over assets. Additionally, I also included 3-digit sector classification and province fix effects. In Column (2) only loans above 25,000 euro are consider. Column (3) exclude loans requested between April 8 and April 24. In Column (4) the dependent variable is the total amount disbursed, among those who requested a loan.

The divergence with the results presented in Section 5.2.1 could have numerous explanations. First, the universe of firms and loans considered are different between the two analyses. Contrary to the Fuzzy-RD design, the before-after exercise concentrates most firms, who ask for small loans. Secondly, the before-after exploits the variation of the policy at the early stages of the pandemic. Hence, firms asking for loans immediately after the Decree's approval could be heavily selected. On the one hand, they could be the worst firms, as they wait until automatically approved loans to ask for them. On the contrary, firms who asked at the beginning of the pandemic, even before the Decree was approved, could be struggling the most, as they could not wait for further economic measures from the government before asking for a loan. As discussed in Section 4.2.1, the former could be biasing the results.

Furthermore, banks considered in this analysis differ significantly from banks who disbursed loans for firms in Section 5.2.1. As Appendix E.2 shows, the majority of Category I loans, which constitute the major part of loans considered in this analysis, are disbursed by one of the big banks. In contrast, for the type of loans considered for the Fuzzy-RD design, non of these banks participated. Even more, the change in incentives for banks is greater when considering the introduction of the policy. Instead of increasing a 10% the risk, there is a risk decrease of 20% in some cases, and an important reduction in screening costs as loans in Category I are automatically approved. Finally, as mentioned in Section 4.2.1, the results of this analysis, although suggestive, could not be interpreted in a causal framework.

As mentioned in Section 2, Category I loans implied a substantial reduction in the operative cost for the banks since they do not have to evaluate the eligibility of the firm with FG standards. Thus, Column (2) presents the results of estimating equation 4 considering only the requests for loans above 25,000. In this case, β_2 and β_3 stopped to be significant, implying that zombie and non-zombie firms do no face different probabilities of getting a loan approved neither before nor after the Decree. The former suggests that zombies requiring bigger loans are likely selected, both before and after. Moreover, it reinforces the hypothesis of Section 5.2.1: a 10% change in incentives to screen is not enough to change bank behavior.

Anticipation effects are another critical feature that could jeopardize my identification strategy. Although the policy did not come into force until April 24, the Decree was announced and approved by April 8. To account for this, in Column (3), equation 4 is estimated considering only firms who request a loan before April 8 and after April 24. The results align with the findings in Column (1), but the absolute value is higher. These could be rationalized if firms requesting loans between April 8 and April 24 are self-selected as the best ones. These firms, knowing that they will obtain a loan anyhow, decided to apply, while the worst firms opted to wait until the Decree is in place. In this case, after April 24, the probability that a zombie firm is getting a loan approved with respect to non-zombie firms is 2.4% pp relatively higher than before the reform.

Finally, Column (4) presents the results of estimating the same regression, considering as a dependent variable the total amount of loan disbursed among those who request for it. Hence, including zero if the loan was not approved. Firms after the reform are concentrating their requests on smaller loans, as indicated by α_1 negative and significant. Moreover, zombies are not over-proportionally getting higher amounts of loans (α_3 is not significant). The former agrees with results in Section 5.1: the policy is fostering zombie lending through a higher amount of loans disbursed to zombie firms, not through more money per loan.

6 Final remarks

Several governments engaged in efforts to provide liquidity to SMEs during the recession originated by the Coronavirus spread. In this paper, I study the allocation across firms of government funds through public guaranteed loans during the Coronavirus crisis. The Italian government introduces profound and unique modifications to the public guaranteed loans scheme to support small firms. Together with the access to loans and firm granular information, the former makes the Italian case a perfect case of study.

First, descriptive analysis shows that loans extended to zombie firms do not differ in their conditions from loans disbursed to non-zombie firms. The heterogeneity between zombie and non-zombie firms comes when considering the type of loan requests. At the beginning of the pandemic, zombie firms were over-proportionally requesting loans in Category I, while they persistently under-requested loans in Category II and III.

Results trying to disentangle financial urgency from strategic behavior suggest that the policy fosters zombie lending in sectors less negatively affected by the pandemic. Moreover, this result is entirely driven by the extensive margin. Zombie firms are over-proportionally asking for loans, but those credits are not of higher magnitude than those requested by non-zombie firms (intensive margin). Results could not be interpreted in a causal framework. Further, to make claims regarding the efficiency of the policy, it is needed to analyze the destination of the founds. Besides, an *ex-post* shock definition of zombie firms, which incorporates the permanent change in the productivity distribution across firms its fundamental to assess if the loans are flowing to the weakest firms.

For estimate if partial insurance systems could prevent zombie lending, I first consider the discontinuity between Category II and III. I find that an increase in screening incentives does not prevent zombie lending. This result could be explained by a small change in incentives in comparison with the increase in screening costs. Moreover, firms around the threshold are heavily selected. Finally, firms could be substituting previous risky debt in agreement with banks. On the other hand, when exploiting the decrease in screen incentives when the policy was introduced, I find that cheaper and easy-to-get loans foster zombie lending. In the last case, results could not be interpreted causally, as firms before the reform could differ from those asking after the Decree.

All in all, this paper suggests that the public loan guarantee scheme introduced to provide firms with liquidity is fostering zombie lending. Moreover, results on bank screening incentives and zombie lending are not conclusive. Future research including the final use of the funds, the debt substitution patterns, and an updated definition of zombie firms *ex-post* the permanent shock, is crucial to be able to evaluate the efficiency of the policy.

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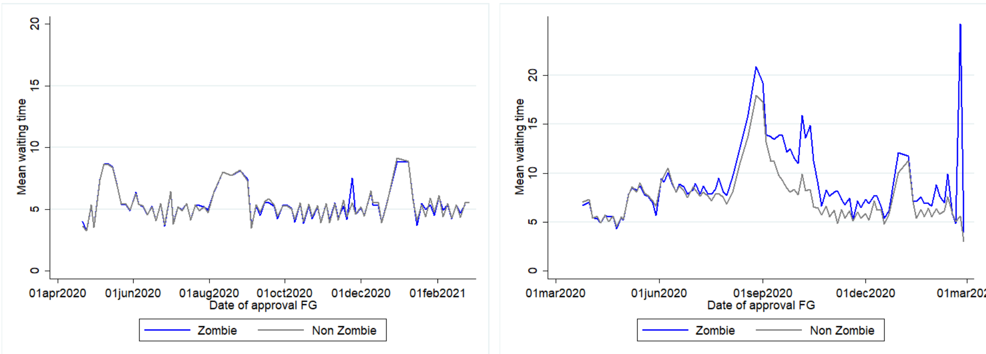
A Zombie lending: descriptive analysis

This section presents an exhaustive comparison in the loan conditions between zombie and non-zombie firms.

Figure 4: Waiting time between the request of the loan to FG and the approval date of FG of the loan: zombie firms by category

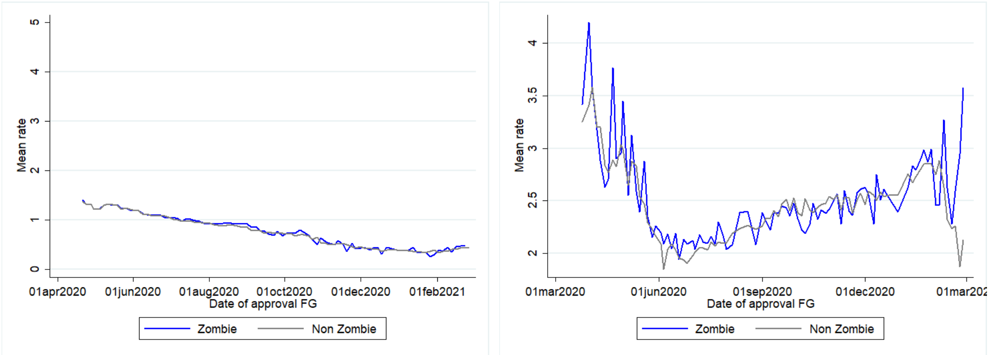


(a) Category I (b) Category II

Figure 5: Mean duration of the disbursed loan: zombie firms by category

(a) Category I (b) Category II

Figure 6: Mean rate of the disbursed loan: zombie firms by category



(a) Category I (b) Category II

B Robustness: zombie firm defined with Altman Z-score

Given the absence of empirical consensus in the definition of zombie firms, in this section results of the main analysis are presented using as definition of zombie firms with high Altman Z-score. The former is an index that tries to identify the firm probability of bankruptcy, computed as:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1X_5$$

Where: X_1 = working capital / total assets; X_2 = retained earnings / total assets; X_3 = earnings before interest and taxes / total assets; X_4 = market value of equity / total liabilities; X_5 = sales / total assets.

The zones of discrimination are:

$$Z \leq 2.99 \Rightarrow \text{safe zone}$$

$$1.81 \leq Z \leq 2.99 \Rightarrow \text{grey zone}$$

$$Z \leq 1.81 \Rightarrow \text{distress zone}$$

CERVED re-scaled from 0 to 9, 9 been "very risky". Zombie firms are defined as firms with scores 7, 8 and 9. Table 5 depicts summary statistic for the comparision of the OECD zombie definition used in the main text and the Altman Z-score definition:

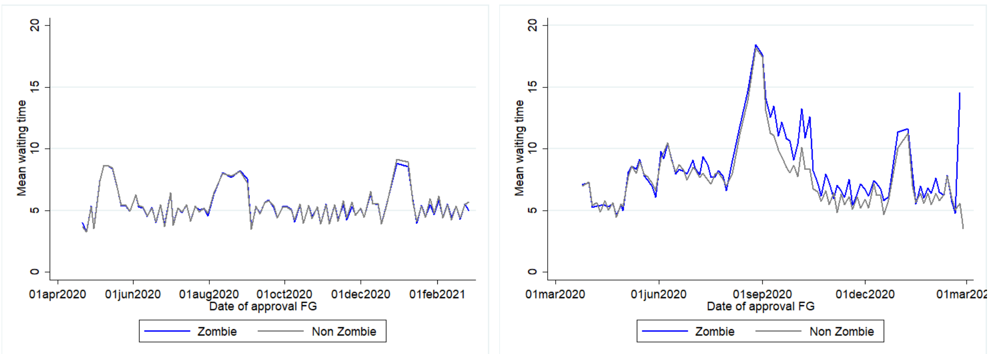
Table 5: Description zombie vs non-zombie firms. OECD and Z-score definition

	OECD			Z-score		
	Observations	Leverage	Sales	Observations	Leverage	Sales
Zombie firms	82,432	416,000	281,000	126,005	271,000	200,000
Non Zombie firms	658,578	210,000	319,000	615,005	219,000	348,000

Under this alternative definition, 16% of the 2019 sample correspond to zombie firms.

B.1 Zombie lending: descriptive analysis Except for Figure 9 in which zombie firms systematically face higher interest payments, the results are robust to alternative definition of zombie.

Figure 7: Waiting time between the request of the loan to FG and the approval date of FG of the loan: zombie firms by category



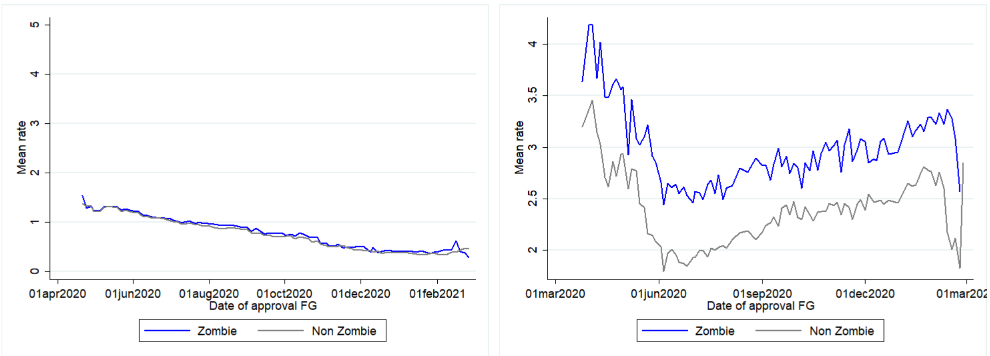
(a) Category I (b) Category II

Figure 8: Mean duration of the disbursed loan: zombie firms by category

(a) Category I

(b) Category II

Figure 9: Mean rate of the disbursed loan: zombie firms by category



(a) Category I

(b) Category II

B.2 Zombie lending and government guaranteed loans

The following Table repeats the estimation of equation 1 with an alternative definition of zombie firms. Results are robust to the ones presented in 5.1.

Table 6: Zombie lending and government guaranteed loans: cross-section

	Total	Extensive Margin				Intensive Margin					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Total	Total	Apr-Jun	Jul-Sep	Oct-Feb	Total	Apr-Jun	Jul-Sep	Oct-Feb	Cat. I	Cat. II
Interaction	15636.6***	0.0691***	0.0447***	0.0514***	0.0512***	-2415.5	-716.2	-4746.6	-6705.1	44.25	-12265.5**
	(1297.7)	(0.00291)	(0.00312)	(0.00301)	(0.00292)	(2379.2)	(2145.0)	(4501.8)	(5220.0)	(74.82)	(5350.1)
Unaffected sector	33726.6***	-0.0654***	-0.0763***	-0.0497***	-0.0286***	33883.4***	37913.3**	30012.8***	26049.4**	577.8***	32125.7***
	(3633.8)	(0.00449)	(0.00497)	(0.00490)	(0.00480)	(9716.5)	(17467.5)	(10585.9)	(11462.0)	(120.6)	(9251.2)
Zombie	-36492.6***	-0.0495***	-0.0161***	-0.0485***	-0.0521***	-38600.7***	-29865.0***	-56055.2***	-32669.1***	-1077.5***	-74135.4***
	(1297.5)	(0.00314)	(0.00345)	(0.00334)	(0.00323)	(2701.6)	(3802.5)	(4422.0)	(5141.0)	(76.15)	(5673.7)
Observations	819959	819969	594871	541525	521947	400772	175677	122335	102760	231900	168872
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

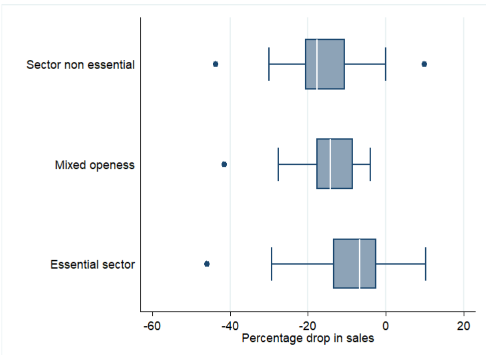
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Correlation between different measures of affectedness

In this section I provide evidence on the link between have been declared essential sector by March 25, 2020 Decree and the drop in sales, predicted by CERVED sectoral experts.

Figure 10: Distribution of sales losses and essential sector at March 25.



Sector declared essential experiment lower drop in sales than non-essential sectors. Table 7 presents the mean average drop in sales depending on the sectoral status by March 25, 2020.

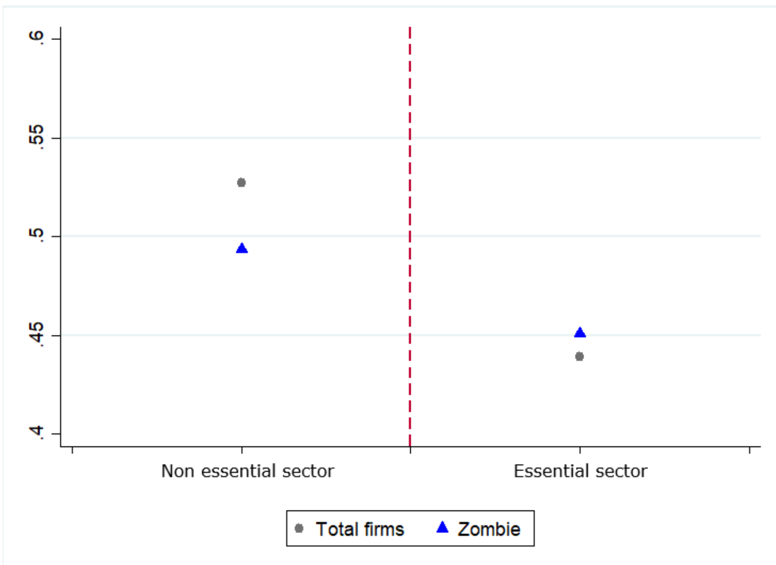
Table 7: Mean in sales drop by essential condition by March 25, 2020

	Mean
Non essential sector	-17
Mixed open	-15
Essential sector	-9

D Zombie lending and government guaranteed loans: motivational graph

In order to provide visual evidence of the reliance of the main hypothesis presented in Section 4.1, Figure 11 presents the proportion of firms that requested a loan by type of sector and zombie status. The grey dots represents the proportion of firms that requested loans. The blue triangles represents the proportion of zombie firms that requested loans.

Figure 11: Proportion of disbursed loans by sector: Zombie vs. Total Firms

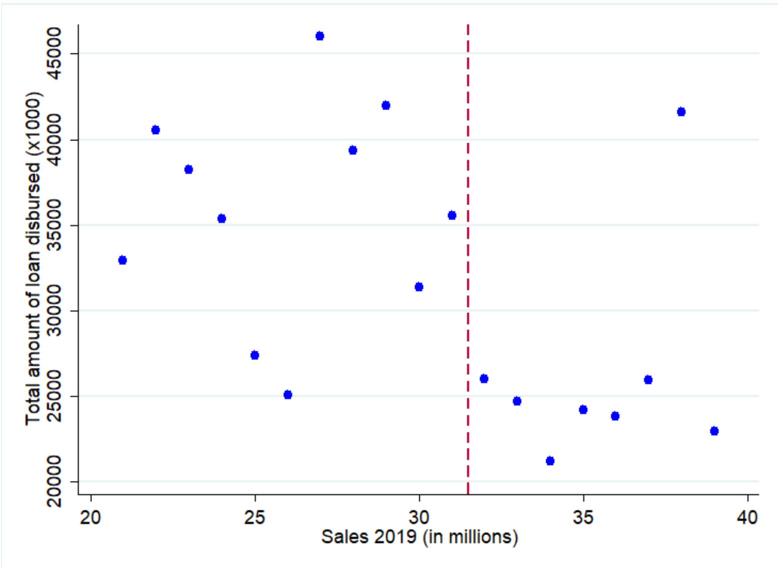


As expected, firms in affected sectors proportionally ask for more loans than firms in unaffected sectors. Moreover, zombie firms over-proportionally requests for loans in unaffected sectors.

E Bank screening and zombie lending

E.1 Fuzzy-RD: visual evidence Figure 11 provides visual evidence of the RD exercise. Firms are grouped by bins of 100,000 sales. Only bins around the 3,2 million euro threshold are presented. Each dot represents the total amount of loans disbursed to loans in each bin.

Figure 12: Amount of disbursed loans by sales



E.2 Bank size and loan disbursement Figure 13 depicts the frequency of loan extended by type of banks (big and small) sorted by loan amount.

Figure 13: Bank behaviour in the disbursement of loans