Conversations with Loan Officers: Policy Intervention and the Functioning of the Credit Market during a Crisis

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Abstract

By using loan officers' forecasts and ex-post retrospective assessments, I study the early impact of both the COVID-19 shock and subsequent policy intervention as a laboratory to improve our understanding of the functioning of the credit market. The qualitative information in the dataset allows me to distinguish demand from supply factors and to look at business, mortgage and consumer loans separately. Estimates show that the shock and subsequent policy measures had a significant impact on the functioning of the Italian credit market, with business loans partially crowding out household loans. Loan and interest rate data combined with a quasi-sperimental setting further corroborate the estimates.

Keywords: COVID-19, Banks, Expectations, Forecasts, Demand, Supply, Credit, Cycle, Crisis, Government policy, Policy evaluation
JEL: C53, D83, D84, E32, E37, E65, G18, G21, G28, G41

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Additional information

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1. Introduction

How a large shock and subsequent policy intervention affect the supply and the demand of bank loans? Are there any differences between business and household loans? A deep understanding of the functioning of the credit market is essential to better understand the transmission of large shocks throughout the economy and to inform how policy makers should approach future crisis. By studying the credit market in the first semester of 2020, I am the first, at least to my knowledge, to provide the point of view of bank officers on that,[1] and by exploiting the sharp discontinuity at the outbreak of the COVID-19 crisis in Italy. The evidence in then tested against lending and interest rate data.

Italy was the first European country hit by the COVID-19 crisis in the first few months of 2020, which makes it a particularly useful environment for studying the effect of the COVID-19 economic shock. The virus appeared unexpectedly in one the most densely populated area of the North-West, to spread to the rest of the country. Severe mobility restrictions and an impressive death toll hit the entire country: COVID-19 was an unprecedented shock for type and magnitude of the events. On March 4 the Italian government fully recognized that the country was exposed to a severe public health risk, the output declined, and the crisis took over. Short after, on April 8, the Italian government announced an important guarantee scheme for business loans.[2]

Nevertheless, the economics of that shock and of subsequent policy intervention are far from being well understood. In the model economy of Faria-e-Castro (2021), for instance, COVID-19 enters as a shock to the marginal utility of service consumption, as consumption is impeded by the lockdown. In Guerrieri et al. (2020), the COVID-19 shock enters the model economy as a negative labour supply shock to one sector, as workers in some sectors stay home either by choice or owing to government-imposed containment. Interestingly, in Guerrieri et al. (2020), credit frictions contribute to the possibility of observing *Keynesian supply shocks*, i.e. supply shocks —probably

[1] For instance, Binder (2020) provides the point view of consumers. See next for a review of the literature.

[2] On this, Altavilla et al. (2021), for instance, studies credit additionality of guaranteed loans in Europe. See next for a review of the literature.

like the COVID-19 economic shock— to which demand overreacts, producing a demand-deficient recession.

Indeed, since the financial crisis in 2008-2009, the financial sector has taken centre stage on the research agenda in academics and elsewhere. Since then, it has been clear that while in normal times the financial sector can mitigate financial frictions, in times of crisis the financial sector's fragility can add to instability. Bank credit plays a central role in Italy. As in other countries, bank credit smooths household consumption against temporary shocks (Morse (2011), DeJuan and Seater (2006)), mortgage loans are an important driver of business cycles (Mian and Sufi (2018)), and business lending has effects on real economic activity (Peek and Rosengren (2000) and Cingano et al. (2016)). Furthermore, bank credit allocates resources not only over time, but also across sectors of the economy, and credit demand, either from households or from firms, can signal which force is driving output fluctuations.

As shown in Figure 1, the Italian credit market was significantly affected by the events in the first few months of 2020, with divergent responses for firms and households. However, interpreting such trajectories is particularly challenging for several reasons. First, a deep understanding of the functioning of the credit market requires an appreciation of the forces of demand and supply, variables that are neither directly observable nor readily inferred. Second, the state of the economy is not easy to know, in that key statistics become available with different lags and time frequencies. Third, early policy efforts add to the shock, making it almost impossible to disentangle the original nature of the shock from the effect of policy intervention. Finally, nearly all economic decisions crucially depend on agents' expectations about future economic outcomes.[3] And when two events follow one another in a short space of time, agents' expectations may be the only economic variable keeping track of both, as the decision process is revised before any action is fully deployed.

Survey data can help to cope with such fundamental issues. Indeed, they can elicit the forces of

[3] As Coibion and Gorodnichenko (2015) put it 'expectations matter', and the credit market is no exception.

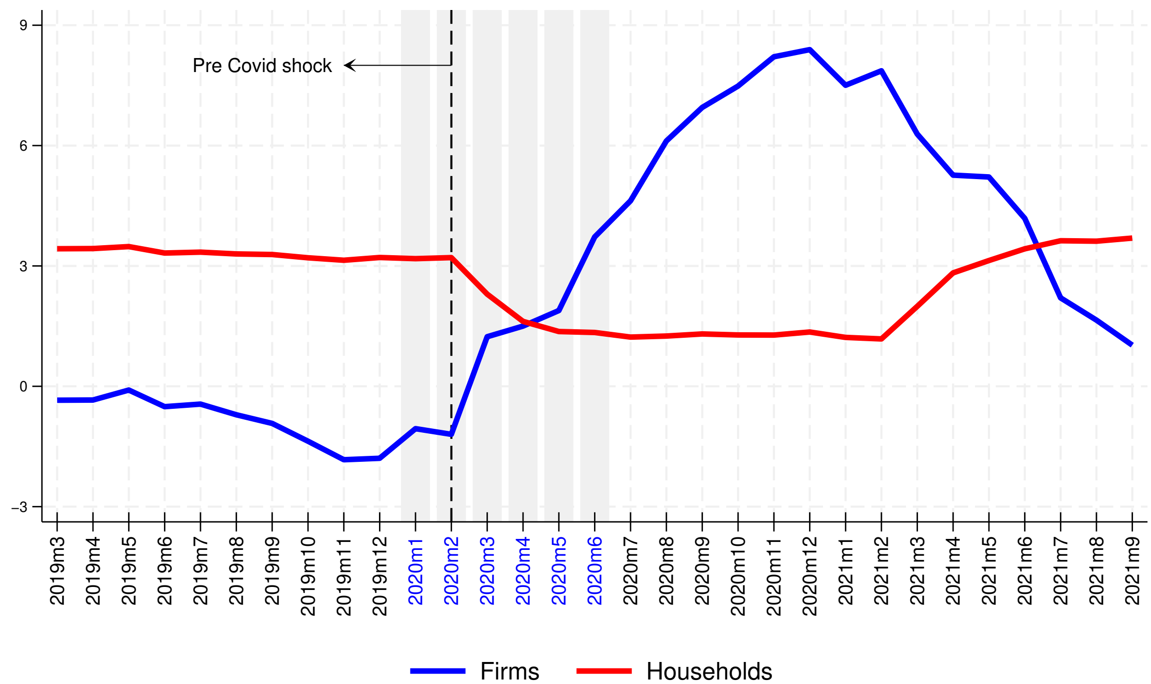

Figure 1: Loans (12-month percentage change).

supply and demand, in addition to agents' expectations, and are promptly available.[4] Thus, a number of studies to which this work is closely related are based on expectations and survey data during the COVID-19 crisis. Binder (2020) studies survey-elicited consumer expectations in connection to the COVID-19 shock and to the FED's interest rate cut announcement and Baker et al. (2020) integrates firm survey data to test how forecasted GDP contraction can be tracked to COVID-19-induced uncertainty. Christelis et al. (2020) investigates the reaction of household consumption to the outbreak of the virus by using survey data. Moreover, Giglio et al. (2021) uses investor survey data to study how expectations shaped the stock market in the COVID-19 period and Gormsen and Koijen (2020) uses market-based data for 2020 to study investors' expectations about future economic growth. In addition, Meyer et al. (2021) uses firm survey data to get the main features of the COVID-19 crisis; Alekseev et al. (2020) surveys SME owners, managers and employees to study the early stages of the crisis; Ferrando and Ganoulis (2020) observes credit access expectations through survey data from a sample of European firms; and Bordalo et al. (2020) surveys COVID-19-related risk perceptions.

[4]Manski (2004) and others advocate the importance of using survey data to test alternative hypotheses.

To make progress on our understanding of the crisis and to help inform how policy makers should approach future crisis, I am the first, at least to my knowledge, to study the COVID-19 shock from the viewpoint of banks. In particular, I use data from the Regional Bank Lending Survey (RBLS), a bi-annual survey by the Bank of Italy. Loan officers[5] —as insiders to the credit market— provide their expectations on the current changes in supply and demand, in addition to their ex-post retrospective assessments on such changes in the subsequent wave of the survey. By looking at the exact time when they made their contemporaneous forecasts, I can obtain qualitative information on how banks' expectations changed following the COVID-19 shock. Indeed, recognition of a full-blown emergency had a focal point in Italy on March 4. Furthermore, policy measures were announced *after* contemporaneous forecasts but *before* retrospective assessments (see Figure 2). Thus, I can also test the role of the events in the last three months of the first semester of 2020 on the functioning of the credit market.

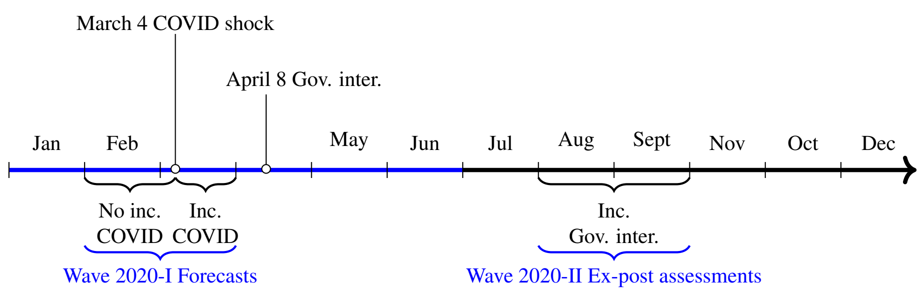

Figure 2: Timeline of the events and structure of the survey.

Therefore, this work provides an important contribution also to the recent literature that uses policy intervention in 2020 as a laboratory to improve our understading of the functioning of the credit market itself and of the effectiveness of policy action passing through it. Altavilla et al. (2021) finds that business loan guarantee programs partially substituted pre-existing non-guaranteed business loans, a resul similar to Jiménez et al. (2022) and Cascarino et al. (2022). The latter uses Italian data and shows that credit additionality of guarantee programs was highest

[5]In this paper I use the terms *loan officer* and *bank officer* interchangeably.

between April and June 2020. Kirti et al. (2023) recognises that most policy actions during the COVID crisis featured a mix of combined interventions, making it difficult to disentagle the effect of a single policy and Minoiu et al. (2022) suggests that the Main Street Lending Program in the US had significant impact on the credit market through a spillover effect that went well beyond its direct —and limited— take-up. In this paper I provide an additional element that must be considered when evaluating policy interventions that target, directly or indirectly, the banking sector: a potential substitution between business and household lending.

Apart from the unique regional breakdown of the data, supply and demand data are indeed also provided separately for the three segments of the credit market: business loans, household mortgages, and consumer credit. This is extremely important in the attempt to appreciate the dominant channels in the transmission of both the COVID-19 shock and subsequent policy measures.

Overall, I find that the COVID-19 shock prompted a downward revision of banks' supply to households. By using bank officers' ex-post retrospective assessments, I also find that the events in the last three months of the first semester of 2020, including an unprecedented public laon guarantee scheme for firms, substantially changed the prospects for the Italian credit market, with a substantial increase in the supply of business loans. However, those events did not overturn the trends in the household credit market where bank supply decreased further, in particular for mortgage loans. The result is consistent with the concentration of public funds in the business credit market, mostly through a sizeable government loan scheme. As of December 2020, almost one fifth of all outstanding business loans were backed by the Italian government.

On the other hand, in relation to the shock, banks' revised firm demand for loans downwards. Although it is not possible to distinguish between business loan demand relating to working capital and that linked to investment, it is likely that banks' forecasts of a substantial downward revision of firms' investment plans drove down credit demand expectations.This speaks both to the nature of the shock and to banks' expected level of operations in the months after the shock.[6] As pointed

[6]This provide a potential explanation for banks not being promptly ready to manage the surge in operations that occurred from mid April onwards.

out also in Kirti et al. (2023), policy intervention can have a significant effect on bank lending even by modifying the demand for credit. And evidence in this work shows that, in the last three months of the first semester of 2020, firm demand for business loans increased significantly while households demand continued to decline.

To better understand the mechanism behind this result, I test two alternative hypotheses: the complementary and the substitution hypotheses. In fact, the public loan guarantee scheme in favour of business loans might have generated a new lending capacity —also to the advantage of household credit— or tilted incentives toward firms, making its final effect on the household credit market ambiguous. Estimates suggest that the increase in supply to firms partially crowded out household credit, supporting the substitution hypothesis.

Thus, the work contributes to the literature along several dimensions. First, it can help interpret lending trajectories in 2020 (see Figure 1). Second, it adds to the literature that stresses the importance of using real-time expectations and survey data in macroeconomic analyses. Third, it can help inform how policy makers should approach future crisis, by also showing a new trade-off potentially involved in their action. Furthermore, it stimulates future research about the transmission channels identified in this work and the role, if any, of over- and under-reaction from loan officers.

The paper is structured as follows. Section 2 introduces the data. Section 3 explains the identification strategy of this work and Section 4 introduces the baseline estimates. Following the robustness checks in Section 5, Section 6 probes the impact of the mix of policy measures deployed in reaction to the emergency and Section 7 considers additional robustness checks. Section 8 concludes.

2. Data source and descriptive analysis

This paper uses data from the half-yearly Bank of Italy *Regional Bank Lending Survey*[7] (RBLS) on banks' forecasts for credit supply and demand for the first semester of 2020. The survey was

[7] Similar surveys include the European central bank's BLS (Berg et al. (2005), Del Giovane et al. (2011), Ciccarelli et al. (2015)) and the Federal Reserve's SLOOS (Schreft and Owens (1991), Lown and Morgan (2006)).

conducted in February and March 2020.[8] Therefore, the forecasts at least partially incorporated the expected impact of the COVID-19 shock. Italy declared a state of emergency on March 4, 2020. In addition, the paper also uses ex-post retrospective assessments of supply and demand for the first semester of 2020, recorded in August and September 2020. The survey covered a large cross section of banks, totaling 377 observations and accounting for about 90 per cent of the Italian household and business credit market. The banks reported expectations separately for the different regions in which they do business: North-West, North-East, Centre and South. Thus, banks operating in more than one region can be considered as separate entities.

The banks' forecasts are summarized, for supply, as 'easing' (1), 'stability' (0), and 'tightening' (-1) with respect to the previous semester, for credit demand, as 'increase' (1), 'stability' (0), and 'decrease' (-1). The original responses of the banks are on a scale from -2 to $+2$, with intervals of 1 point. However, Orame (2023) shows that the use of data on the intensity of the change can be controversial, as what appears to be a strong change in the eyes of one loan officer may be seen as mild by others, threatening internal consistency.

Loan data are from the 'Credit and Financial Institutions' Supervisory Reports' of the Bank of Italy[9] and COVID-19 contagion data are provided by the 'Presidenza del Consiglio dei Ministri-Dipartimento di Protezione Civile' open data project on the matter.

To appreciate forecasting data on supply and demand, I first resort to net percentages. Net percentages show how many banks report a change in supply (demand), and they are obtained by the simple difference between the share of banks reporting an easing in credit standards[10] and the share of those reporting a tightening (share of banks reporting an increase in demand and the share of those reporting a decrease[11]). Net percentages are a well-known descriptive tool and, in this

[8]Two banks returned the questionnaire late, on April 8 and 9.

[9]Interest rate data are from a special section of the Credit register of the Bank of Italy and cover a subsample of banks and loans.

[10]Credit standards shape the supply policy of a bank.

[11]On the supply side it is more common to report the difference between the share of banks reporting a tightening and of those reporting an easing. However, to make things more intuitive, I report the difference between the share of banks reporting an easing and of those reporting a tightening. By using this convention, an easing or increase in supply shows up with a positive sign, exactly like an increase in demand.

setting, positive values are considered a proxy for an upward shift in supply or demand.[12]

Table 1 shows key summary statistics of banks' forecasts for the entire first semester of 2020, as of February-March 2020. The Table displays minor changes in the supply of loans and an overall increase in their demand. In the rest of the paper, I will rely on a simple average of the responses instead of net percentages: Table 1 shows that, in this specific setting, the two measures are equivalent.

Table 1: Distribution of banks' forecasts for the first half of 2020

	SUPPLY			DEMAND		
VALUES	Firms	H'hold mortg.	H'hold consum.	Firms	H'hold mortg.	H'hold consum.
DECREASE (-1)	0.08	0.03	0.04	0.23	0.15	0.09
UNCHANGED (0)	0.88	0.91	0.91	0.49	0.54	0.62
INCREASE (1)	0.04	0.06	0.05	0.28	0.31	0.29
NET PERCENTAGE	-0.04	0.03	0.01	0.05	0.16	0.22
MEAN	-0.04	0.03	0.01	0.05	0.16	0.22

Raw data. The net percentage is the simple difference between the share of banks reporting an easing of supply and of those reporting a tightening (or between the share of banks reporting an increase in demand and the share of those reporting a decrease). Positive values for the indicator are a proxy for an easing of supply (increase in demand). Negative values for the indicator are a proxy for a tightening of supply (decrease in demand). More details are available in Appendix A.

3. The empirical strategy

The survey, conducted in February and March 2020, at least partially incorporated the impact of the COVID-19 economic shock on banks' expectations for the first semester of 2020. However, the data in Section 2 cannot be directly related to that shock for several reasons.

First, banks may have formulated their expectations at different times within the two-month window of the survey. Awareness of the contagion changed significantly during this period: some banks may have fully incorporated the prospect of the pandemic while others did not. This variation will actually be at the core of the identification strategy of this work.

Second, perception of the pandemic may have changed not only over time but also across regions.

[12] See Bassett et al. (2014).

Banks do business in different regions and the contagion progressed unevenly across the country. Banks that formulated their expectations at the same time may have factored in the pandemic differently, depending on the overlapping of the spread of the virus with their own areas of business. Third, overoptimism or an excess of pessimism can contaminate the results; see Brunnermeier and Parker (2005) and Van den Steen (2004). Thus, I elaborate more on these three points in the next three subsections.

3.1. March 4 and the timing of forecasts

Italy was the first European country hit by the virus. Therefore, differently from other European countries, anticipatory bias might be limited, making Italy a particularly useful environment for studying changes in expectations in relation to the COVID-19 shock. Figure 3 shows that the contagion took off early in March. Even more importantly, on March 4 the Italian government introduced new restriction measures that applied for the first time to the entire nation. The Prime Minister's emergency decree 14241/2020[13] aimed at containing the spread of the virus by means of strict social distancing measures, including the nationwide closure of all schools. This was a focal point for people's expectations concerning the COVID-19 emergency, an event that made the entire nation aware of the severity of the crisis.[14]

In the questionnaire, there was no such a thing as a field for date of compilation. That makes it difficult to grasp the moment in which banks formed their expectations, an essential piece of information. For that reason, this paper scrapes banks' files to get the last date on which the questionnaire was saved before transmission to the Bank of Italy. Indeed, this date is an even more faithful indication of the time when banks updated their supply and demand expectations than the date that could have been obtained with a dedicated field. Figure 4 shows that banks formed their expectations at different times. About one third of the banks made their forecasts after March 4,

[13] https://www.governo.it/sites/new.governo.it/files/DPCM4MARZO2020.pdf

[14] Twitter data from the first six months of 2020 show that after the news from China and some initial discussion over the allegedly unique case of infection in the province of Lodi—in the North-West of the country—the COVID-19 focal point was in the first ten days of March, see Figure B.6 in Appendix B.

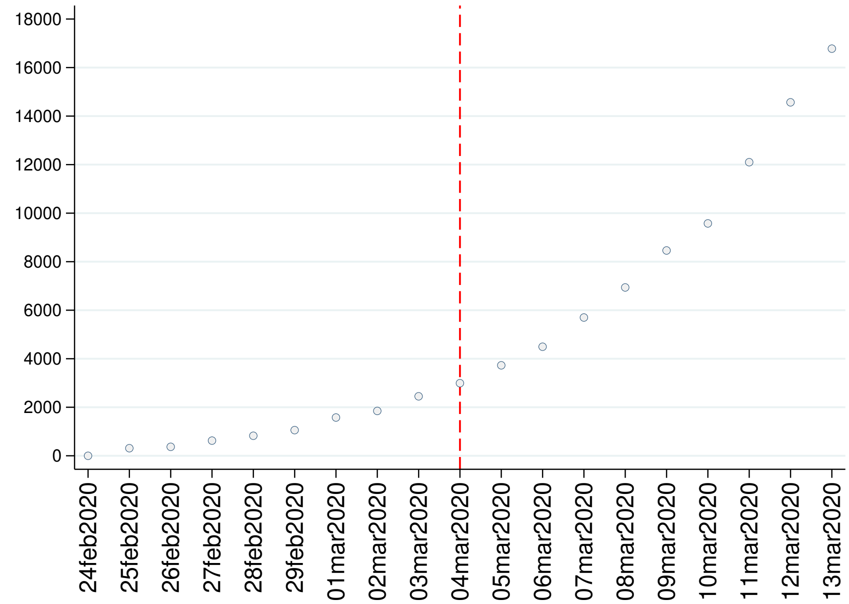

Figure 3: Progress of the contagion: number of cases.

with a full-blown emergency under way. Others formed their expectations before the declaration of the emergency and they did not incorporate the prospect of the crisis. A controlled comparison of pre and post March 4 forecasts is at the core of the empirical strategy of this paper.

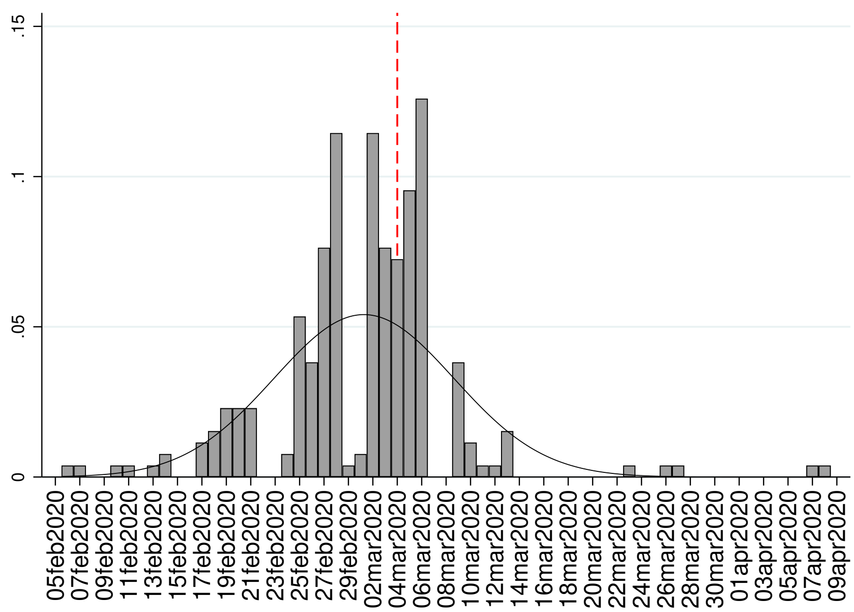

Figure 4: Day of formation of supply and demand expectations for 2020h1.

3.2. *The geography of the pandemic*

The contagion progressed unevenly across the country. The first cases were recorded in the most populated areas of the North-West. The virus rapidly reached other regions in the North-West and North-East, but not in the Centre and South, which were less affected by the pandemic in the early stages of the crisis. Despite the declaration of the emergency being nationwide —a fact that further confirms that restriction measures were largely unexpected— banks may have had a different take on the pandemic depending on their area of business. Nonetheless, survey data comes with a regional breakdown as banks reported their expectations separately for the different regions in which they do business. These regions are North-West, North-East, Centre and South and the richness of the dataset allows me to compare bank expectations formulated for the same region.

3.3. *Expectation bias*

Bias in forecasts can be important. Beliefs affect managerial decisions, and their systematic distortion can explain part of the variations in the data; see Ma et al. (2020). However, a comparison of pre and post March 4 forecasts already absorbs any bias common to all banks. In addition, the paper compares regional data, with the potential for absorbing biases specific to a region. Even more importantly, to assuage any residual concern about the interpretation of the results, I computed the individual mean difference between expectations and ex-post assessments before the COVID-19 shock over more than ten years of the survey. By interpreting that as an idiosyncratic bias, I subtracted it from forecasts in 2020. Thus, this work is more informative about the nature of the COVID-19 shock, and less so about any connection between forecasting biases (overoptimism or overpessimism) and economic outcomes, a subject that is left to future research.

4. The shock and the change of expectations: phase 1

In this Section, I use the announcement of March 4 to study how the COVID-19 shock affected banks' expectations. Banks likely reviewed their plans along the way — even before any action was fully deployed— and so I can better isolate the effect of the COVID-19 shock through the lenses of bank officers' expectations.[15] Figure 5 shows that banks' expectations may have changed immediately after the declaration of a state of emergency on March 4, and I test this hypothesis with the following model:

$$\mathbb{E}_{2020h1}[\Delta y_{b,r}^{2020h1}] = \alpha + \beta_1 PostMar4_b + \beta_2 X_{b,r} + \psi_r + \varepsilon_{b,r} \tag{1}$$

where y is a shorthand for $Demand/Supply$ forecasts for the first semester of 2020 made by bank b with respect to region r. Banks predict the *change* in supply and demand (Δy). $PostMar4_b$ is a dummy equal to one if bank b formed its expectations after March 4, thus whether expectations incorporated the prospect of the COVID-19 pandemic. $X_{b,r}$ are bank- and bank-region level controls, as of December 2019, that will be used to test the robustness of the estimates. To compare forecasts on the same local credit market, the model includes ψ_r, a full set of region fixed effects. The analysis is done separately for business loans, household mortgage, and consumer credit. In fact, a detailed study of the three segments of the credit market can shed light on the transmission mechanisms of the COVID-19 shock and subsequent policy intervention.

To test for any change in banks' expectations that can be related to the COVID-19 economic shock, I first estimate Equation 1. Further robustness checks are presented in Sections 5 and 7. Table 2 shows the estimates of β_1 for supply and demand forecasts in the three segments of the credit market. These coefficients tell us how forecasts for the first semester of 2020 were revised in relation to the COVID-19 shock.

The estimates in Column 1 do not take into account regional differences. Column 2 adds area fixed effects and Column 3 clusters the standard errors at the bank level. Finally, Column 4 adjusts loan officers forecasts for their idiosyncratic overoptimistim or overpessimism and is the baseline

[15] Rodrez Mora and Schulstad (2007) shows that updating of expectations is informative about the future developments of the economy.

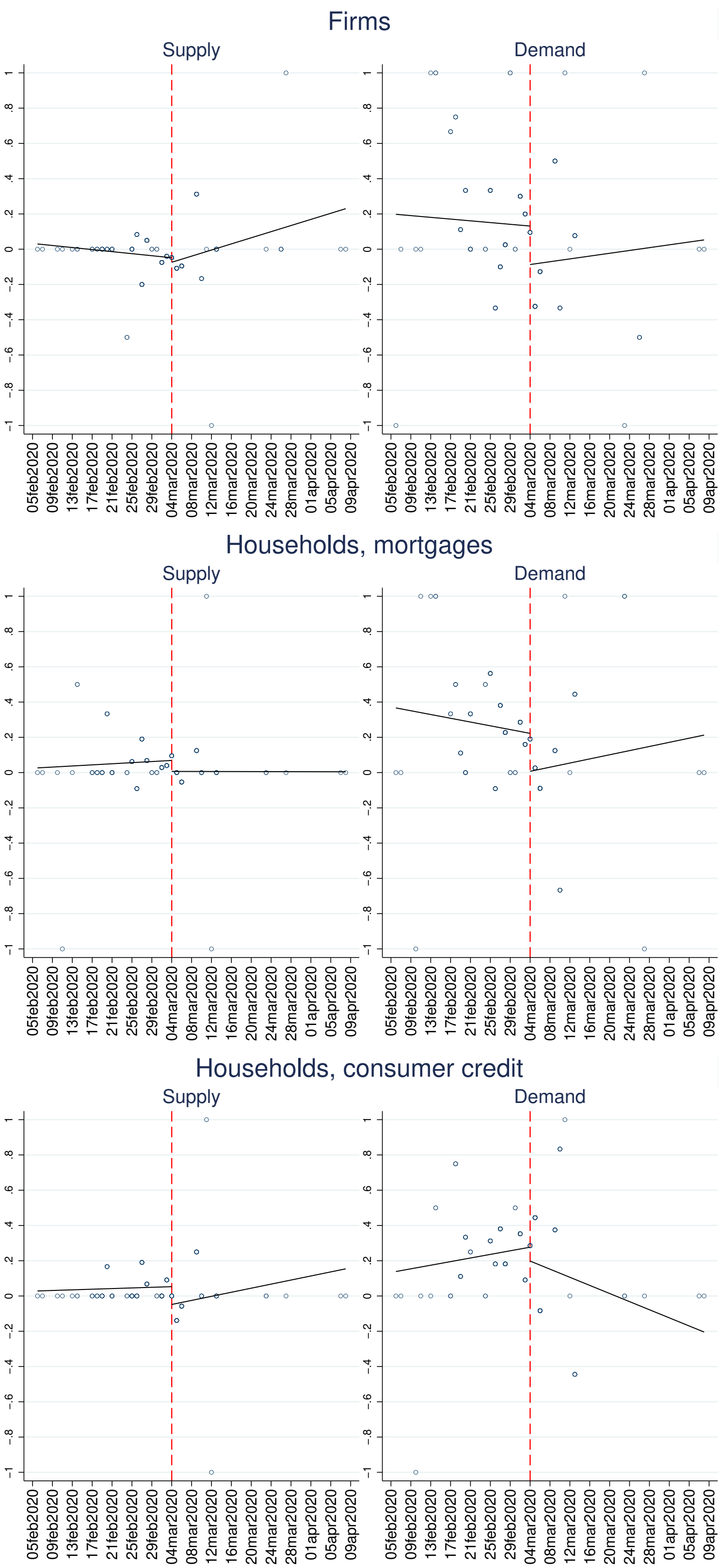

Figure 5: Daily means. Forecasts of supply and demand changes reported by banks.

estimate of this paper. In particular, for each bank-area, I compute the average difference between forecasts and ex-post assessments between 2009 and 2019, and I use it to adjust forecasts in 2020.[16] The discrete event on March 4, a focal point in 2020, prompted a significant change in banks' expectations about the developments of the credit market in the first semester of 2020. The changes are heterogeneous between segments of the credit market. Furthermore, the empirical evidence supports the view that those effects are related to the declaration of the emergency and thus to the original nature of the COVID-19 economic shock, at least as seen from the point of view of bank officers.

Rows 1 to 3 of Table 2 show the estimates for the supply of loans. The coefficient for the post-March-4 dummy is not significantly different from zero for business loans. Thus, banks did not significantly revise their expected business loan supply to firms for the first semester of 2020 after the COVID-19 shock. However, they revised their expected supply to households downwards, for both mortgages and consumer credit. On the supply side, the shock seems to bite more on households rather than on firms.

Rows 4 to 6 of Table 2 show the estimates for the demand for loans. The coefficient for the post-March-4 dummy is negative and statistically significant for the demand for business loans. Although the data do not allow a distinction to be made between loan demand relating to working capital and that linked to investment, it is likely that banks' forecasts of a substantial downward revision of firms' investment plans drove down overall credit demand expectations. This speaks both to the nature of the shock and to banks' expected level of operations in the months after the shock, providing also a potential explanation for banks not being promptly ready to manage the surge in operations occurring from mid April onwards. For mortgage household loans, the estimates of a decline in demand are not robust while, for consumer loans, demand expectations remained largely unchanged. In essence, banks' expectations for household demand in the second semester of 2020 were not significantly revised after March 4. On the demand side, the shock seems to bite more on

[16] I use more than twenty waves of the survey. This adjustment is important because optimistic loan officers may have systematically updated their assessments before pessimistic loan officers did, thus biasing the results.

firms rather than on households.

Thus the estimates show the impact of the COVID-19 shock on the credit market from the point of view of bank officer expectations, and suggest that this impact cannot be directly inferred by a simple reading of raw survey data from Table 1, which would provide an inaccurate picture of the functioning of the credit market in connection to the outbreak of the virus.

Table 2: Main results.

DEP. VARIABLE	(1)	(2)	(3)	(4) BENCH.	(5)	(6)	(7)
Δ Supply Firms	-0.010	0.013	0.013	0.003	-0.019	0.012	0.004
	[0.0375]	[0.0398]	[0.0538]	[0.0522]	[0.0655]	[0.0536]	[0.0524]
Δ Supply h'hold mortg.	-0.067**	-0.055	-0.055*	-0.083**	-0.083*	-0.070*	-0.073*
	[0.0331]	[0.0357]	[0.0326]	[0.0379]	[0.0479]	[0.0383]	[0.0377]
Δ Supply h'hold consum.	-0.108***	-0.100***	-0.100	-0.159***	-0.175**	-0.151***	-0.165***
	[0.0336]	[0.0362]	[0.0625]	[0.0564]	[0.0693]	[0.0581]	[0.0580]
Δ Demand Firms	-0.242***	-0.273***	-0.273**	-0.341***	-0.340**	-0.342***	-0.351***
	[0.0753]	[0.0803]	[0.1204]	[0.1172]	[0.1385]	[0.1201]	[0.1200]
Δ Demand h'hold mortg.	-0.254***	-0.252***	-0.252**	-0.220*	-0.216	-0.219*	-0.230*
	[0.0714]	[0.0769]	[0.1204]	[0.1252]	[0.1513]	[0.1271]	[0.1282]
Δ Demand h'hold consum.	-0.106	-0.106	-0.106	-0.116	-0.077	-0.110	-0.116
	[0.0647]	[0.0694]	[0.1108]	[0.1150]	[0.1305]	[0.1168]	[0.1171]
Area FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
S.E. bank clustered	No	No	Yes	Yes	Yes	Yes	Yes
Bias correction	No	No	No	Yes	Yes	Yes	Yes
Time elapsing control	No	No	No	No	Yes	No	No
Bank exposure control	No	No	No	No	No	Yes	No
Without March 4	No	No	No	No	No	No	Yes

Standard errors in parenthesis. Firm: 365 obs. H'hold mortg: 349 obs. H'hold consum.: 340 obs. Time elapsing control: days elapsing from March 4. Bank exposure control: province level infections weighted by bank-province total loans. * p < 0.1, ** p < 0.05, *** p < 0.01.

To confirm the discrete nature of the event on March 4, Columns 5 to 7 further challenge the estimates. Column 5 controls for the passage of the days. The passage of the days is measured from March 4, normalizing that date to 0. The estimates further support the discontinuity marked by March 4 also when taking into account of the normal passage of time. Indeed, all the estimates remain statistically significant, with the sole exception of household mortgage demand.

Column 6 adds a different control as the virus was spreading unevenly across the country. Thus, not passage of the days in itself is measured, but the spread of the virus over time where banks do business. To absorb this time-varying bank-region specific confounding factor, Column 6 uses the exposure indicator $E_{b,r}$. More precisely, $E_{b,r}$ is the bank-specific exposure to the pandemic in region r by bank b, as at the time it was forming its expectations, where the cases of infections in each province are weighted by the loan share of bank b in province p over loans in region r. (Note that banks already provide supply and demand assessments for region r). In Equation 2, C_p are the number of infections in province p and $L_{b,p}$ are outstanding loans by bank b in province p. The estimates in Column 6 show further evidence in support of the identification strategy in this work, because the insights provided by the post-March-4 dummies are not altered by the introduction of the new indicator.

$$E_{b,r} = \sum_{p \in r} C_p \frac{L_{b,p}}{\sum_{p \in r} L_{b,p}} \tag{2}$$

Column 7 drops March-4 forecasts, thus addressing the concern that March-4 forecasts are not easily assigned either to the pre- or to the post-announcement period.[17] Once again, the sign and significance of the estimates are not affected, showing that the results are robust to several perturbations of the benchmark setting.

5. Did banks' characteristics affect the estimates? Robustness Checks

Other latent factors can still contaminate inference. To address residual concerns surrounding identification, I add dummies relating to key banks' characteristics. In practice, supply changes might have been different between pre- and post-March-4 regardless of the pandemic if the banks forming their expectations in the two sub-periods had been systematically different. In particular, to exclude the estimates from just being a by-product of banks' characteristics, Column 1 in Table 3 uses a dummy equal to one for banks with a top-quartile ratio of capital to total assets, measuring distance from regulatory insolvency. Column 2 uses a dummy for the ratio of deposits to total loans

[17]Considering that the announcement occurred within the 24 hours of March 4, it is plausible that some forecasts on that day were performed before and others after the announcement. Thus, from this point of view this test is also known as 'donut test', see Barreca et al. (2011). Further robustness checks of this kind are shown in Section 7.

and Column 3 resorts to a dummy equal to one for banks with a ratio of profits to total assets in the top quartile of the sample distribution. Finally, Column 4 resorts to a dummy for the logarithm of total assets controlling for the specific behaviour of large banks. All balance sheet data are as of December 2019 and the results are essentially unchanged. By also considering the continuous measures of capital, liquidity, profitability and size, the outcome is virtually unchanged. Thus, the empirical evidence rules out the possibility that the results are driven by systematic differences between banks forming their expectations before and after March 4.

Although the regional breakdown of the data already provides a full set of area fixed effects, banks can still be different in how they do business within each area. In fact, estimates can be contaminated if pre- and post-March-4 banks have a systematically different market power in the region. To rule out that possibility, Columns 5-6 in Table 3 use geographical dummies that vary at the bank-area level. In particular, Column 5 uses a dummy equal to one for banks in the top quartile of the market share distribution within a region[18] and Column 6 does the same by resorting to the number of provinces within a region in which a bank operates,[19] both as of December 2019.[20] The insights remain unchanged and I can reach similar conclusions by resorting to the continuous measures behind geographical dummies. The evidence is therefore consistent with the view that the unique geographical breakdown in the data already absorbs any factor relating to the regions in which a bank does business. To help assuage any remaining identification concerns, Section 7 uses all controls at the same time by means of a propensity score matching and shows that banks' characteristics do not drive the estimates.

Finally, Column 7 in Table 3 addresses the concern that the results may reflect other events rather than the direct effect of the COVID-19 shocks. In fact, some banks formed their expectations between the end of March and the first days of April, when other confounding events may have occurred. In particular, five banks formed their expectations after March 17, the date in which the first of a series of policy measures was announced. Column 7 shows the estimates from the

[18]The market share is computed on the outstanding stock of total loans.

[19]A bank operates in a region if it lends to at least one customer that is based on that region.

[20]Appendix A shows key descriptive statistics for those variables.

baseline model in which those observations are discarded. The outcome is virtually unchanged, signaling that those observations are not an issue for the interpretation of the results. Additional robustness checks are shown in Section 7.

Table 3: Robustness checks.

DEP. VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Supply Firms	0.007	0.006	0.006	0.006	-0.002	-0.000	-0.008
	[0.0519]	[0.0519]	[0.0528]	[0.0555]	[0.0564]	[0.0545]	[0.0535]
Δ Supply h'hold mortg.	-0.082**	-0.082**	-0.093**	-0.078*	-0.066*	-0.078**	-0.082**
	[0.0392]	[0.0378]	[0.0404]	[0.0399]	[0.0394]	[0.0394]	[0.0387]
Δ Supply h'hold consum.	-0.157***	-0.155***	-0.163***	-0.154***	-0.139***	-0.145***	-0.163***
	[0.0560]	[0.0556]	[0.0575]	[0.0508]	[0.0462]	[0.0484]	[0.0580]
Δ Demand Firms	-0.312***	-0.336***	-0.320***	-0.281**	-0.266**	-0.289**	-0.329***
	[0.1125]	[0.1174]	[0.1168]	[0.1169]	[0.1142]	[0.1149]	[0.1214]
Δ Demand h'hold mortg.	-0.206*	-0.2223*	-0.253**	-0.157	-0.195	-0.169	-0.224*
	[0.1239]	[0.1241]	[0.1199]	[0.1275]	[0.1220]	[0.1251]	[0.1272]
Δ Demand h'hold consum.	-0.110	-0.119	-0.132	-0.051	-0.090	-0.075	-0.108
	[0.1131]	[0.1135]	[0.1142]	[0.1008]	[0.1018]	[0.1014]	[0.1181]
Capital	Yes	No	No	No	No	No	No
Liquidity	No	Yes	No	No	No	No	No
Profitability	No	No	Yes	No	No	No	No
Size	No	No	No	Yes	No	No	No
Market share	No	No	No	No	Yes	No	No
Presence	No	No	No	No	No	Yes	No
Confounding events	No	No	No	No	No	No	Yes

Standard errors in parenthesis. Standard errors clustered at the bank level. Firm: 365 obs. Column (7): 357 obs. H'hold mortg.: 349 obs. Column (7): 344 obs. H'hold consum.: 340 obs. Column (7): 335 obs. H'hold consum. supply: 340 obs. Capital: capital to total assets, dummy equal to one for banks in the top quartile. Liquidity: deposits to total loans, dummy equal to one for banks in the top quartile. Profitability: profits to total assets, dummy equal to one for banks in the top quartile. Size: logarithm of total assets, dummy equal to one for banks in the top quartile. Market share: share of loans in the region, dummy equal to one for banks in the top quartile. Presence: share of provinces in the region where the bank lend to customers, dummy equal to one for banks in the top quartile. Data as of December 2019. Column (7) discards banks that formed their expectations after March 17. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. After the shock: phase 2

The first semester of 2020 was characterized by the pandemic shock on March 4, by the unfolding of the pandemic and by a mix of policy actions, some of them targeting directly the credit market and the banking sector. The number of deaths peaked on March 27, to decline to almost zero by the end of the semester. On March 18, the European Central Bank (ECB) announced the Pandemic Emergency Purchase Programme (PEPP) under which it decided to buy public and private sector bonds in the secondary market. On April 30, it also announced a new series of Pandemic Emergency Longer-term Refinancing Operations (PELTROs) to support liquidity conditions in the financial system.

However, the most important event for the Italian credit market occurred on April 8, when the Italian government announced a series of measures[21] that included an unprecedented public loan guarantee scheme for firms.

Thus, the revision of banks' expectations around March 4 did not factor in those events. However, in August and September 2020, banks were asked to report their overall ex-post retrospective assessment of the change in credit supply and demand for the first semester of 2020, in which they also factored in the events in the last three months of the semester.

Although I am mindful that this is not experimental data, and that it is not possible to distinguish the effect of a single policy measure from that of the others and from any unexpected progression of the contagion, I can still get new insights on the developments of the credit market from the point of view of loan officers. In fact, if by comparing pre- and post-March-4 expectations I can produce an estimate of the effect of the COVID-19 shock on the credit market, by comparing post-March-4 expectations with retrospective assessments in August and September 2020 I can get a sense of the overall effect on the credit market of the events that occurred in the last three months of the semester with an eye of the most important one: the unprecedented public loan guarantee scheme for firms through which almost almost one fifth of all outstanding business loans were backed by the Italian government by the end of 2020.

[21] Some of those measures were already foreseen on March 17.

6.1. The empirical strategy

To study the developments in the credit market in the last three months of the first semester of 2020, I estimate the following equation:

$$\Delta y_{b,r}^{2020h1} = \beta_1 \mathbb{E}_{2020h1}[\Delta y_{b,r}^{2020h1} | \Omega_{t<=March4}] + \beta_2 \mathbb{E}_{2020h1}[\Delta y_{b,r}^{2020h1} | \Omega_{t>March4}] + \psi_r + \varepsilon_{b,r} \tag{3}$$

where y is a shorthand for $Demand/Supply$ (at the bank-region level) and ψ_r are region fixed effects. Ex-post retrospective assessments as of August and September 2020 for the first semester of 2020 are regressed on banks' expectations[22] for the same semester formed in February and March, allowing for different coefficients based on the information set on which such expectations had been formed, i.e. before or after the pandemic shock on March 4, 2020. I then obtain the residuals from this regression, i.e., $\Delta y_{b,r}^{2020h1} - \Delta\hat{y}_{b,r}^{2020h1}$. The residuals mainly contain the unexpected component of the ex-post assessments and they mostly reflect the update on the developments of the credit market due to the events in the last three months of the first semester of 2020.

6.2. The estimates

Table 4 shows the average of the residuals, for both the entire sample and for the subsample of banks that factored in the pandemic shock in their post-March-4 expectations. The estimates show a further and significant change in the credit market in the last three months of the first semester of 2020 and identify a second phase of the crisis.

[22] As before, expectations are adjusted by an estimate of overoptimism or overpessimism at the bank-region level. Appendix C shows the estimates from a simple difference between forecasts and ex-post retrospective assessments, first without adjusting expectations, Table C.11, and then by adjusting expections, Table C.12. Results are essentially unchanged.

Table 4: Residuals.

RESIDUALS	ALL SAMPLE (1)		POST MARCH 4 (2)	
Δ Supply Firms	0.048	[0.0328]	0.107**	[0.0519]
Δ Supply h'hold mortg.	-0.019	[0.0183]	-0.067**	[0.0305]
Δ Supply h'hold consum.	-0.020	[0.0218]	-0.046	[0.0449]
Δ Demand Firms	0.152***	[0.0414]	0.253***	[0.0684]
Δ Demand h'hold mortg.	-0.125***	[0.0402]	-0.262***	[0.0681]
Δ Demand h'hold consum.	-0.124***	[0.0397]	-0.258***	[0.0662]

Standard errors in parenthesis. Firms: 356 obs. Restricted sample 141 obs. H'hold mortg.: 340 obs. Restricted sample 128 obs. H'hold consum.: 330 obs. Restricted sample: 129 obs. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Rows 1 to 3 of Table 4 show the estimates for the supply of loans. The supply of business loans took a different path from the one initially expected in March. Although banks predicted that they would not change their supply of business loans, the events in the last three months of the semester prompted them to increase their supply of loans to firms. On the other hand, the supply of loans to household decreased more than initially expected, in particular for mortgage loans.

Rows 4 to 6 of Table 4 show the estimates for the demand for loans. The events in the last three months of the first semester of 2020 completely overturned demand expectations. Business loan demand increased unexpectedly. On the other hand, the demand for household loans decreased significantly in the last part of the semester.[23]

6.3. *Supply changes: hypothesized mechanism*

From April 2020, banks, differently from what they initially planned for the first semester of 2020 after the COVID-19 shock, significantly increased their supply of business loans. Firms increased their demand. During these months, firms benefited from an important public business loan guarantee scheme.[24] Less well understood is whether the scheme had an impact on the household credit market.

[23] For context, note that mobility, after a trough in the first decade of April following severe mobility restrictions imposed in March, started to recover, hoovering half-way pre-crisis levels already in May, see Google mobility report data in Appendix D.

[24] Twitter data from the first six months of 2020 show that the focal point for government intervention in the credit market was in the first decade of April, see Figure B.6 in Appendix B. At the end of 2020, almost one fifth of all outstanding business loans were backed by the Italian government.

On the one hand, the public guarantee scheme on business loans might have generated new lending capacity, free to spill over into the household credit market (*complementarity*). On the other hand, the increased size of the business loan market might have diverted funds toward this segment of the credit market (*substitution*). Thus, the overall effect on the household credit market remains ambiguous. As a concrete example, consider a bank that significantly increased its supply of business loans in the last three months of the first semester of 2020: did it reduce or increase, if anything, its loan supply to households?

To test the substitution-complementarity hypothesis, I combine supply residuals from Equation 3 for business, mortgage and consumer credit in order to study banks' behaviour. To do that, I estimate the following equations where y is a shorthand for supply:

$$\Delta y_{b,r,mort}^{2020h1} - \Delta \hat{y}_{b,r,mort}^{2020h1} = \alpha_1 + \beta_1(\Delta y_{b,r,bus}^{2020h1} - \Delta \hat{y}_{b,r,bus}^{2020h1}) + \psi_b + \varepsilon_{b,r} \tag{4}$$

$$\Delta y_{b,r,cons}^{2020h1} - \Delta \hat{y}_{b,r,cons}^{2020h1} = \alpha_2 + \beta_2(\Delta y_{b,r,bus}^{2020h1} - \Delta \hat{y}_{b,r,bus}^{2020h1}) + \psi_b + \varepsilon_{b,r} \tag{5}$$

The unexpected supply change in the household credit market for the last three months of the first semester of 2020 is put in relation to the unexpected supply change in the business loan market. To exclude alternative interpretations, I include bank-fixed effects to absorb any idiosyncratic bank factor that could contaminate inference. In fact, the unique geographical variation in the dataset makes it possible to control for time-invariant bank characteristics that can affect the supply strategy of a bank. Thus, the estimates will exploit the within-bank variation in the dataset by looking at the behaviour of the same bank in two different regions. Complementarity of firm and household credit must show up in a positive β_1 or β_2. On the contrary, if they are substitutes or, in other words, if a supply increase to firms crowds out loan supply to households, β_1 or β_2 must be negative. Finally, if there are no spillovers between the two segments of the credit market, these coefficients must not be statistically different from zero.

Table 5: Testing supply changes relating to emergency measures.

DEP. VARIABLE	SUPPLY MORTGAGE		SUPPLY CONSUMER	
	(1)	(2)	(3)	(4)
Supply Firms	-0.342***	-0.342***	-0.314***	-0.314***
	[0.0260]	[0.0176]	[0.0448]	[0.0273]
N	104	104	104	104
R-squared	0.9977	0.9977	0.9961	0.9961
Bank FEs	Yes	Yes	Yes	Yes
S.E. bank clustered	No	No	Yes	Yes

Dependent variables: residuals from Equation 3 for mortgage and consumer loan supply data. Regressor: residuals from Equation 3 for business loans. Standard errors in parenthesis. * < 0.1, ** p < 0.05, *** p < 0.01.

Table 5 tests the complementarity-substitution hypothesis between firm and household credit both for mortgage and consumer loans. The estimates in Column 1 and 3 show a negative sign for both β_1 and β_2. Furthermore, the estimates are statistically significant and, as shown in Column 2 and 4, robust to alternative clustering of the standard errors. Thus, the empirical evidence supports the view that the events in the last three months of the first semester of 2020 generated a partial substitution effect between business and household loans.

6.4. Bank-province level data

Although it is not possible to fully isolate supply factors, I provide indirect evidence supporting the substitution hypothesis using lending and interest rate data. First, I use monthly growth rates of lending to households and to firms in the 2019m10-2020m9 twelve-month window around March 2020.[25] In the estimating Equation 6, the dependent variable is the monthly growth rate of loans to households for bank b in province p in month t, put in relation to the monthly growth rate of loans to firms for the same bank b and in the same province p in month t. The flexibility of the research design allows the correlation to vary over time by virtue of the interaction with a dummy equal to one from April 2020 onwards. Province fixed effects ψ_p —or province-time fixed effects $\psi_{p,t}$— potentially absorb demand factors and ψ_b control for any idiosyncratic bank factor common to all

[25] Loan growth rates are adjusted by the effects of securitizations, reclassifications and other variations that are not a result of ordinary transactions. Data include bad loans and loans under a repurchase agreement.

provinces that can contaminate inference. Therefore, inside one province, the model compares —across banks— how the province-specific variation in lending to firms relates to the province-specific variation in lending to households.

$$\Delta L_{b,p,t}^{\%,h'hold} = \alpha + \beta_1 AprOnw_t + \beta_2 \Delta L_{b,p,t}^{\%,firms} + \beta_3 AprOnw_t * \Delta L_{b,p,t}^{\%,firms} + \psi_p + \psi_b + \varepsilon_{b,p,t} \tag{6}$$

Table 6: Lending growth rates, household loans.

	(1)	(2)	(3)	(4)
$\Delta L_{b,p,t}^{\%,firms}$	.036**	.031***	.0297***	.0297***
	[.0145]	[.0111]	[.0109]	[.0109]
$AprOnw_t$	-.363***	-.446***		
	[.1252]	[.1327]		
$AprOnw_t * \Delta L_{b,p,t}^{\%,firms}$	-.027**	-.026**	-.026**	-.026**
	[.0121]	[.0108]	[.0107]	[.0107]
$\Delta L_{b,p,t}^{\%,firms} + AprOnw_t * \Delta L_{b,p,t}^{\%,firms}$				0.004
				[0.0036]
N	149.034	149.029	149.029	149.029
R-squared	.0027	.0320	.0339	.0410
Province FEs	Yes	Yes	Yes	No
Bank FEs	No	Yes	Yes	Yes
Time FEs	No	No	Yes	No
Province-time FEs	No	No	No	Yes

Dependent variable: monthly growth rates of loans to households (percentage). Standard errors in parenthesis. Standard errors clustered at the bank level. Household and firm growth rates outside the 1-99th percentiles are dropped from the sample. * p < 0.1, ** p < 0.05, *** p < 0.01.

Column 3 in Table 6 shows that the growth rates of lending to households and firms are positively correlated. However, the coefficient on the interaction term with the April-onwards dummy is negative and statistically significant, supporting the substitution hypothesis. In fact, the appropriate test shows that, following policy interventions, loans to households and to firms were no longer correlated.

To assuage residual identification concerns, I further challenge the estimates with a different specification. In fact, province fixed effects absorb time-invariant factors, including demand factors that remain constant over time, but survey data suggest that household credit demand changed over time in the twelve-month window of this exercise. Thus, I probe the estimates by introducing province-time fixed effects instead of province fixed effects, because they can better absorb household demand. The results in Column 4 of Table 6 are virtually unchanged with respect to Column 3. Thus, if lending to firms and households had previously moved together, this was no longer the case from April onwards.

Table 7: Interest rates, household loans.

	(1)	(2)	(3)	(4)	(5)
$\Delta L^{\%,firms}_{b,p,t}$	-.003	-.003**	-.002**	-.003*	-.002*
	[.0029]	[.0013]	[.0013]	[.0014]	[.0013]
$AprOnw_t$	-.262***	-.272***			
	[.0527]	[.0514]			
$AprOnw_t * \Delta L^{\%,firms}_{b,p,t}$	.001	.003**	.003**	.003**	.003**
	[.0030]	[.0012]	[.0012]	[.0014]	[.0013]
$\Delta L^{\%,firms}_{b,p,t}$+$AprOnw_t * \Delta L^{\%,firms}_{b,p,t}$				0.000	0.000
				[0.001]	[0.001]
N	5529	5526	5526	5526	5526
R-squared	.0761	.3362	.3376	.3714	0.4163
Province FEs	Yes	Yes	Yes	No	No
Bank FEs	No	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	No	No
Province-time FEs	No	No	No	Yes	Yes
Additional controls	No	No	No	No	Yes

Dependent variable: interest rates charged to new household loans (percentage). Standard errors in parenthesis. Standard errors clustered at the bank level. Interest rates and firm growth rates outside the 1-99th percentiles are dropped from the sample. To guarantee data quality, interest rate data must be available at time t and at time t-1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Although interest rate data are only available for a subsample of banks, and at a quarterly frequency, I use them to provide further indirect evidence in support of the substitution hypothesis. In particular, in Equation 6, I substitute the dependent variable, the growth rate of household loans, with the interest rate charged to new household loans.[26] Thus, in one province, the model compares —across banks— how the province-specific variation in lending to firms relates to the interest rate charged to new household loans in that province, once the average interest rate applied by a bank in all provinces is netted out.

Column 4 in Table 7 shows that a higher growth rate of loans to firms is associated with a reduction

[26]Data are available for new term loans above €75,000.

in the interest rate charged to households. In other words, an expansion in firm loans is generally associated also with a relaxation of the conditions applied to households. However, the coefficient on the interaction term with the April-onwards dummy is negative and statistically significant, breaking this link from April onwards. Thus, also this estimate does not reject the hypothesis that the increase in the supply of business loans partially crowded out household loans.

Nevertheless, in the same province, two banks can also offer different loan terms to household, thereby contaminating inference. For this reason, Column 5 in Table 7 includes, as bank-province controls, the share of new loans with a maturity of up to one year; the share of new loans with a maturity between one and five years; the share of new loans with a maturity between five and ten years; and the share of consumer loans over total household loans, i.e. several detailed features of household loan origination by bank b in province p at time t. The results are virtually unchanged with respect to Column 4, further supporting the evidence in this Section.

7. Further robustness checks

In Section 5, I performed several robustness checks to challenge the estimates of the impact of the COVID-19 shock on the credit market. In this Section, to further test those estimates, I resort to a propensity score matching to compare pre- and post-March-4 expectations. The dimensionality reduction in the propensity score allows me to overcome the constraint imposed by the overall limited size of the dataset by comparing expectations between banks that are similar not only with respect to a single bank characteristic, as already done in Section 5, but according to the full set of indicators. This will be particularly helpful in assuaging residual identification concerns, in particular those relating to credit supply. In fact, the propensity score centres on the probability of forming expectations before or after March 4, dealing directly with the issue of self-selection.

To match banks with similar business models, I use top-quartile dummies for capital to total assets, deposits to total loans, profits to total assets and logarithm of total assets. I also include a top-quartile dummy for market share at the regional level and a top-quartile dummy for the number of provinces in a region where a bank does business. All data are as of December 2019.

Table 8 in Column 1 contains the propensity score estimates[27] of the revision of expectations for the first semester of 2020 that can be related to the COVID-19 shock. The results are confirmed, showing that there are no systematic differences between banks that can contaminate inference.

Another issue is the possibility that the banks may have *anticipated* the outbreak of the crisis. In this case, the results could not be attributed directly to the COVID-19 shock. Column 2 of Table 8 excludes the forecasts made in the last seven days prior to 4 March 2020 —that is, all the questionnaires with expectations formed between 26 February and 4 March 2020. The results are virtually unchanged with respect to Column 1, confirming that the announcement on March 4 was not anticipated.

As a final concern, I test the possibility that the estimates in this study are the by-product of any mechanical feature of the data. To address this concern, I resort to a falsification test by *randomizing* the date when the banks made their supply and demand forecasts. Column 3 of Table 8 displays the estimates and most of them are not statistically significant. Thus, this exercise confirms the pivotal role played by the different information sets on which banks formed their expectations in the identification strategy of this work.[28]

[27] I report the Average effect of Treatment of the Treated (ATT).

[28] In a similar vein, I also moved the March-4 threshold back or forward by seven days and the estimates are not statistically significant.

Table 8: Propensity score estimates.

DEP. VARIABLE	(1)	(2)	(3) FALS.
Δ Supply Firms	-0.007	-0.004	-0.023
	[0.0450]	[0.0436]	[0.0489]
Δ Supply h'hold mortg.	-0.080**	-0.075	-0.021
	[0.0367]	[0.0458]	[0.0373]
Δ Supply h'hold consum.	-0.151***	-0.132***	-0.071*
	[0.0364]	[0.0341]	[0.0401]
Δ Demand Firms	-0.219***	-0.310***	0.117
	[0.0779]	[0.0886]	[0.0854]
Δ Demand h'hold mortg.	-0.221***	-0.259**	-.011
	[0.0812]	[0.1054]	[0.0836]
Δ Demand h'hold consum.	-0.077	-0.031	0.104
	[0.0690]	[0.0892]	[0.0675]

Average treatment effect on treated banks. Adjusted bank forecasts (see Section 3). Standard errors in parenthesis: bootstrapped standard errors with 1000 replications. Propensity score: probit model and stratification matching with capital, liquidity, profitability, size, presence and market share dummies. Dummies equal to one for banks in the top quartile of the sample distribution. Capital: capital to total assets. Liquidity: ratio of deposits to total loans. Profitability: profits to total assets. Size: logarithm of total assets. Presence: number of provinces in the region where a bank do business. Market share: total loans market share of a bank in the region. Data are as of December 2019. For each segment of the credit market, the analysis includes only banks with no missing observations for both supply and demand. The analysis uses Becker and Ichino (2002). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

8. Final remarks

To elicit the effect of the COVID-19 shock on the functioning of the Italian credit market from the point of view of bank officers, I use banks' expectations and retrospective assessments for the first semester of 2020 from the *Regional Bank Lending Survey* (RBLS) of the Bank of Italy. Centering on the discontinuity at the announcement of unprecedented mobility restrictions on March 4, I find that banks significantly revised their expectations and that the functioning of the credit market had two phases within the first semester of 2020: one immediately after the shock, the other from April onwards.

After the shock on March 4, banks revised their expected loan supply to households and their expected demand for business loans downwards.

The unfolding of the pandemic and the subsequent policy measures—including an important public business loan guarantee scheme thanks to which almost one fifth of all outstanding business loans were backed by the Italian government by the end of 2020—completely overturned trends in the credit market. Banks increased their supply of business loans, and firms increased their demand for credit. However, loan supply to household decreased further, in particular for mortgage loans, and household demand declined.

To better understand the mechanism behind this result and under the guidance of survey-based evidence, I test the complementarity-substitution hypothesis between firm and household supply using lending data. Banks that expanded their supply of credit to firms more, were also more conservative in the supply of household credit, suggesting that the events in the last three months of the first semester of 2020 partially crowded out household credit in favour of business loans. Interest rate data further corroborates the supply interpretation of the estimates.

Thus, this work helps to interpret the dynamics in the credit market during the COVID-19 crisis and show a new potential mechanism at work behind policy intervention in the credit market. It also provide guidance on future theoretical and empirical research, which is still needed to fully understand and quantify the effect of large shocks and subsequent policy action in the credit market.

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Appendix A. Summary statistics

Table A.9: Raw data, demand and supply: summary statistics.

	N	Mean	1st quartile	Median	3rd quartile	Std Dev.
			FORECASTS			
Δ Supply Firms	365	-0.036	0.000	0.000	0.000	0.350
Δ Supply h'hold mortg.	349	0.034	0.000	0.000	0.000	0.301
Δ Supply h'hold consum.	340	0.006	0.000	0.000	0.000	0.307
Δ Demand Firms	367	0.049	0.000	0.000	1.000	0.715
Δ Demand h'hold mortg.	349	0.158	0.000	0.000	1.000	0.657
Δ Demand h'hold consum.	344	0.215	0.000	0.000	1.000	0.587
			EX-POST ASSESSMENTS			
Δ Supply Firms	373	0.139	0.000	0.000	1.000	0.615
Δ Supply h'hold mortg.	349	-0.063	0.000	0.000	0.000	0.350
Δ Supply h'hold consum.	357	-0.123	0.000	0.000	0.000	0.432
Δ Demand Firms	373	0.601	0.000	1.000	1.000	0.729
Δ Demand h'hold mortg.	349	-0.490	-1.000	-1.000	0.000	0.730
Δ Demand h'hold consum.	356	-0.522	-1.000	-1.000	0.000	0.681

Table A.10: Controls: summary statistics

	N	Mean	1st quartile	Median	3rd quartile	Std Dev.
			BANK LEVEL			
Post	262	0.313	0.000	0.000	1.000	0.465
Capital	262	11.577	9.442	11.002	13.330	3.253
Liquidity	262	108.483	95.288	107.008	118.244	37.344
Profitability	262	0.420	0.236	0.418	0.600	0.415
Size	262	21.051	20.188	20.831	21.504	1.462
			AREA-BANK LEVEL			
NORTH-WEST						
Market share	87	1.137	0.072	0.194	0.555	3.326
Presence	87	78.437	60.000	88.000	100.000	23.478
Exposure	87	3.221	0.228	0.902	2.020	7.578
NORTH-EAST						
Market share	127	0.782	0.113	0.207	0.383	2.409
Presence	127	74.946	59.091	81.818	100.000	26.016
Exposure	127	0.690	0.015	0.099	0.710	2.156
CENTRE						
Market share	83	1.187	0.099	0.190	0.745	3.764
Presence	83	78.916	59.091	81.818	100.000	22.252
Exposure	83	0.269	0.006	0.057	0.185	0.674
SOUTH						
Market share	80	1.225	0.052	0.149	0.874	3.515
Presence	80	56.776	22.368	40.789	100.000	37.105
Exposure	80	0.150	0.003	0.028	0.054	0.524

Capital: capital to total assets. Liquidity: deposits to total loans. Profitability: profits to total assets. Size: logarithm of total assets. Market share: share of loans in the region. Data as of December 2019. Presence: share of provinces in the region where the bank lend to customers. Exposure: province level infections weighted by bank-province total loans. Data as of formation of expectations. Percentage points. Exposure: number of cases.

Appendix B. Twitter data

Figure B.6 shows the share of tweets relating to COVID-19 and Government intervention (business loans). COVID-19 tweets must contain at least one of these words: 'coronavirus', 'covid-19', 'covid19', 'covid2019'. Tweets about government intervention in the business loan market must contain at least one of these words: 'prestito garantito' (guaranteed loan), 'aiuto imprese' (firm support), 'liquidità' (liquidity) or 'decreto liquidità' (liquidity decree).

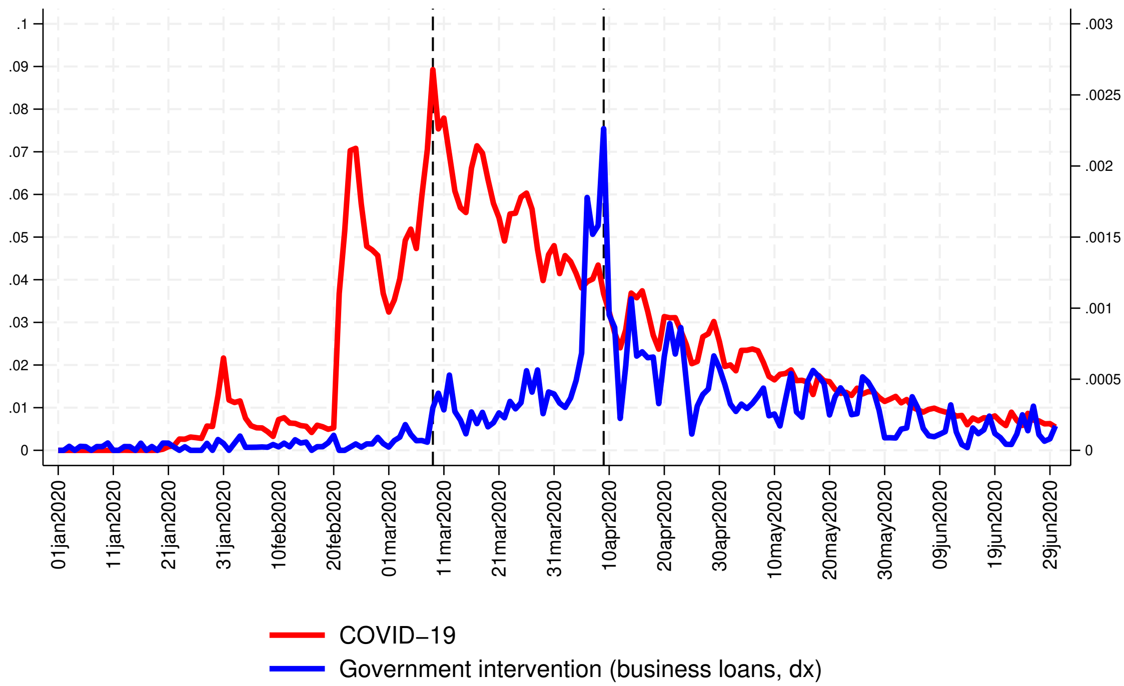

Figure B.6: Tweets, daily data.

Appendix C. Unexpected changes: robustness checks

Table C.11: Unexpected changes: simple difference with raw data.

COR. DIFFERENCES	ALL SAMPLE (1)		POST MARCH 4 (2)	
Δ Supply Firms	0.185***	[0.0351]	0.227***	[0.0545]
Δ Supply h'hold mortg.	-0.100***	[0.0222]	-0.109***	[0.0372]
Δ Supply h'hold consum.	-0.100***	[0.0261]	-0.078	[0.0512]
Δ Demand Firms	0.553***	[0.0514]	0.702***	[0.0797]
Δ Demand h'hold mortg.	-0.647***	[0.0473]	-0.578***	[0.0789]
Δ Demand h'hold consum.	-0.703***	[0.0471]	-0.698***	[0.0783]

Standard errors in parenthesis. Firm: 356 obs. Restricted sample 141 obs. H'hold mortg. : 340 obs. Restricted sample 128 obs. H'hold consum.: 330 obs. Restricted sample: 129 obs. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.12: Unexpected changes: simple difference with 'expecation bias' correction.

DIFFERENCES	ALL SAMPLE (1)		POST MARCH 4 (2)	
Δ Supply Firms	0.0272***	[0.0348]	0.304***	[0.0549]
Δ Supply h'hold mortg.	-0.067***	[0.0221]	-0.058†	[0.0363]
Δ Supply h'hold consum.	-0.046*	[0.0261]	-0.006	[0.0483]
Δ Demand Firms	0.648***	[0.0506]	0.821***	[0.0797]
Δ Demand h'hold mortg.	-0.540***	[0.0468]	-0.487***	[0.0783]
Δ Demand h'hold consum.	-0.581***	[0.0468]	-0.576***	[0.0783]

Standard errors in parenthesis. Firm: 356 obs. Restricted sample 141 obs. H'hold mortg. : 340 obs. Restricted sample 128 obs. H'hold consum.: 330 obs. Restricted sample: 129 obs. † p-value: 0.1135; one-sided p-value testing for the difference being < 0: 0.0567. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D. Google mobility report data

Figure B.6 shows how visitors to categorized places change compared to baseline days. A baseline day represents a normal value for that day of the week. The baseline day is the median value from the 5-week period January 3 – February 6 in 2020.

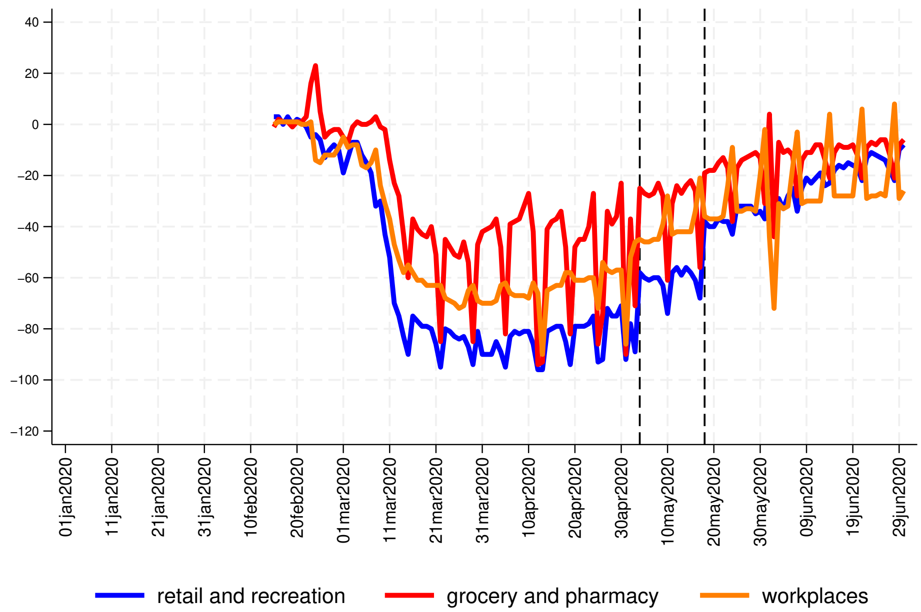

Figure D.7: Google mobility report, daily data.