ISSN 1745-8587

Birkbeck Centre for Applied Macroeconomics

BCAM 1703

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February 2017

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December 5, 2016

Abstract

We study the impact of economic uncertainty on the supply of bank credit using a monthly dataset that includes all loan applications submitted by a sample of 650,000 Italian firms between 2003 and 2012. We find that an increase in aggregate uncertainty has three effects. First, it reduces banks' likelihood to accept new credit applications. Second, it lengthens the time firms have to wait for their loans to be released. Third, it makes banks less responsive to fluctuations in short-term interest rates, weakening the bank lending channel of monetary policy. The influence of uncertainty is relatively stronger for poorly capitalized lenders and geographically distant borrowers.

Keywords: uncertainty, credit supply, bank lending channel, loan applications.
JEL classification: E51, G21.

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The paper has benefited from insightful discussions with Ugo Albertazzi, Nick Bloom, Lorenzo Burlon, Chris Edmond, Leonardo Gambacorta, Giorgio Gobbi, Elisa Guglielminetti, Filippo Mezzanotti, Valentina Michelangeli, Stefano Neri, Steven Ongena, Matthew Plosser, Enrico Sette, Guillaume Vuillemey and seminar participants at Banca d'Italia, the Einaudi Institute for Economics and Finance, the 2016 European Finance Association annual meeting, the 2016 Melbourne Institute Macroeconomic Policy Meeting on "The Macroeconomics of Uncertainty and Volatility". Any errors and omissions are the responsibility of the authors. The views expressed in this paper are those of the authors and do not reflect the position of Banca d'Italia.

1 Introduction

Economic crises generate uncertainty but they also feed on it. As the prolonged recessions that followed the financial crises of 2008-2012 demonstrate, economic volatility brings about a widespread reluctance to borrow, lend and invest that can significantly slow down the recovery.[1] The relation between uncertainty, credit and investment is complex because uncertainty can act through both the demand and the supply side of credit markets. If their choices are irreversible, firms may choose to invest and borrow less when uncertainty is high (Bernanke, 1983; Bloom, 2009; Bloom *et al.*, 2012). Yet creditors face the same problem: corporate loans – their own investments – are risky and irreversible too, and they clearly become less attractive when firms' prospects grow more uncertain (Arellano *et al.*, 2012; Christiano *et al.*, 2014; Gilchrist *et al.*, 2014). This raises a natural question: is the slow-down in bank lending observed in 'uncertain times' a pure by-product of the firms' own choices, or does it also reveal a financial acceleration effect, as increasingly hesitant lenders force firms to borrow less than they would like to? If this is the case, which firms end up bearing the costs of such a shift in banks' lending strategies?

In this article we answer these questions by exploiting the microeconomic data available from the Credit Register of the Bank of Italy. We construct a loan-level dataset that tracks at a monthly frequency the outcome of all new loan applications submitted by a sample of 650,000 nonfinancial firms between 2003 and 2012 and combine it with bank and firm balance sheet data. We then examine the impact of various measures of aggregate uncertainty on (i) the probability that firms' applications get approved and (ii) the time firms have to wait to receive their loans conditional on being successful. Approval probabilities are a measure of the extensive margin of credit supply that has been widely exploited in the banking literature to disentangle supply from demand dynamics, while delays in banks' credit granting decisions are studied here for the first time. We also study the relation between uncertainty and the bank lending channel of monetary policy (Bernanke and Gertler, 1995; Kashyap and Stein, 2000). The motivation is straightforward. Nonfinancial firms are known to respond less to changes in fundamentals when uncertainty is high (Guiso and Parigi, 1999; Bloom *et al.*, 2007). Banks might in principle be subject to a similar wait-and-see type of behavior, and if this is the case their response to shifts in monetary policy might be muted when uncertainty is high.

The identification of a genuine influence of uncertainty on the supply of bank credit faces a number of complications. Credit demand may change heterogeneously across firms in response to uncertainty shocks, depending *inter alia* on the firms' financial constraints (Alfaro *et al.*, 2016).

[1] The research on the topic is reviewed below. For the policy side of the debate, see FOMC (2008), Blanchard (2009), Buti and Padoan (2013).

The quality of the potential borrowers may worsen in bad times, giving banks an independent reason to be less accommodating (Bernanke and Gertler, 1989). Furthermore, uncertainty may propagate differently depending on the banks' business models, including the strength of their existing relationships (Chodorow-Reich, 2014; Bolton *et al.*, 2016). We get around these problems by combining two simple ideas. The first one is to exploit the granularity of the dataset, and the fact that firms typically apply for funds to a number of different banks at once, to introduce in the regressions time-varying fixed effects that vary at the firm level, thus controlling for changes in observed and unobserved firm characteristics as well as general business cycle conditions (Gan, 2007; Khwaja and Mian, 2008; Jimenéz *et al.* 2012, 2014). The second one is to focus on bank capital as the key source of heterogeneity in the intermediaries' behavior, while controlling extensively for other bank characteristics. With frictional capital markets, leverage constraints increase the value of banks' equity rendering them effectively more risk averse (Froot *et al.* 1993, Froot and Stein, 1998). Banks' net worth is indeed likely to be a key driver of their response to changes in the level of aggregate risk in the economy (Brunnermeier *et al.*, 2012, Adrian and Shin, 2014). It follows that, if uncertainty matters at all, it must matter more for thinly capitalized lenders. Once combined, these modelling choices ultimately lead us to analyze the impact of uncertainty on the applications submitted by a given firm at a given point in time to banks that differ in their capital buffers, and hence in their willingness and capacity to bear additional aggregate risk.

We have three main findings. First, a rise in aggregate uncertainty reduces the approval rate for firms' loan applications: a one standard deviation increase in the Economic Policy Uncertainty index of Baker *et al.* (2015), for instance, causes a drop in firms' approval probability from 21 to about 19 per cent. Second, even successful firms must wait longer for their loans to be released when uncertainty is high. Interestingly, interest rates do not have this effect: the length of a bank's decision-making process appears to be affected by its confidence about the future but not by monetary policy in and by itself. Third, uncertainty weakens the bank lending channel of monetary policy. These mechanisms are quantitatively significant: the direct effects of uncertainty are comparable to those of monetary policy itself, and the interaction between the two is such that the bank lending channel essentially disappears in very volatile environments. They also display interesting cross-sectional patterns. Besides operating more through less capitalized banks, uncertainty has a stronger impact on firms that are geographically distant from the bank to which they place their applications. From a firm's perspective, physical proximity turns out to be a better hedge against uncertainty shocks than a good credit rating.

Our main contribution to the literature is to leverage on high-quality microeconomic data to study the causal link between uncertainty and credit supply. Our dataset allows us to track both approved and rejected loan applications, rather than focusing on changes in credit flows observed ex-post, and to study within-firm outcomes, checking how applications placed simultaneously by the same firm are treated by banks with different capital ratios (and hence a different appetite for bearing aggregate risk). This makes it possible to move from a somewhat speculative interpretation of the patterns in the data to a more stringent discourse on causality. In this process we also highlight a dimension of banks' lending policies that as far as we know has not been examined in the banking literature thus far, namely the banks' speed in processing loan applications. This timing dimension sheds more light on the overall implications of uncertainty, and also on the peculiarity that sets uncertainty aside from other factors that also affect bank decisions, including monetary policy. A third complementary contribution we offer to the literature is a thorough investigation of the interaction between uncertainty and the traditional bank lending channel of monetary policy. Economic uncertainty might in principle matter because of its influence on the transmission of monetary shocks, as well as its direct negative effect on credit supply, and this possibility has been largely overlooked thus far.

The remainder of the paper is structured as follows. In Section 2 we review the relevant literature. Section 3 introduces our dataset and presents a set of stylized facts on the behavior of credit applications and approvals in Italy between 2003 and 2012. We then move to the econometric analysis. We begin by studying the dynamics of the loan approval rate, which provides a direct link between our work and existing studies of the transmission of monetary policy based on loan-level data (e.g. Jiménez *et al.*, 2012, 2014). Section 4 presents our key results as well as a set of robustness tests. In Section 5 we switch from the probability of approval to the second dimension of interest, namely the timing of the banks' decisions. Section 6 discusses further identification and robustness issues and Section 7 concludes. The annex to the paper provides additional estimation results and background material.

2 Related literature

Uncertainty rises sharply in or ahead of economic slowdowns (Bloom, 2014). Risk-aversion naturally pushes consumers to save more in riskier environments, causing a decline in economic activity (Bansal and Yaron, 2004; Fernandez-Villaverde *et al.* 2011). This basic precautionary motive can be reinforced by two types of mechanisms.[2] The first one relates to technology: with non-convex capital adjustments costs, a rise in volatility pushes firms to postpone investment

[2] We limit our discussions to frameworks where risk affects the economic cycle, but causality could in principle run in the opposite direction – see e.g. Bachmann and Moscarini (2012).

and hiring decisions because it increases the likelihood that these will have to be reversed in the future (Bernanke (1983), Bloom (2009), Bloom *et al.* (2012)). The second one relates to financial markets: a rise in uncertainty increases firms' default probabilities and benefits equity holders at the expense of debt holders, and this in turn causes an increase in credit spreads, which must rise to compensate creditors for bearing more risk (Arellano *et al.,* 2012; Christiano *et al.*, 2014; Gilchrist *et al.*, 2014).

These theories place different frictions at the centre of the transmission mechanism and lead to opposite conclusions as to which side of the credit market is affected the most by uncertainty. In the 'real view' uncertainty translates into a shock to the demand for credit. In the 'financial view', on the other hand, uncertainty shifts the supply curve by making lenders *ceteris paribus* less willing to provide whatever funds firms may require. Importantly, the frictions that underpin the financial view can also affect the demand side of the credit market. Alfaro, Bloom and Lin (2016) and Chen (2016) show that financially-constrained firms are more sensitive to uncertainty.[3] The impact of credit constraints on firm behavior appears to be quantitatively relevant both in the USA (Alfaro *et al.*, 2016; Chen, 2016) and in other advanced economies (Choi *et al.*, 2016). These results suggest that the identification problem posed by the tension between real and financial view is a particularly hard one to solve. Identifying a genuine credit supply effect on the basis of aggregate, sectoral or even bank-level data is essentially impossible: at those levels of aggregation one cannot credibly rule out the possibility that the contraction in credit that follows a rise in uncertainty is caused by the choices of the borrowers rather than those of the lenders.

Microeconometric studies of uncertainty have mostly focused on nonfinancial firms and on idiosyncratic rather than aggregate uncertainty measures. Leahy and Whited (1996) and Bloom *et al.* (2007) document a strong relationship between stock price volatility and investment for manufacturing firms listed respectively in the USA and in the UK. Guiso and Parigi (1999) measure subjective uncertainty using the distribution of the firms' own expectations on future demand, and find this to have a negative impact on investment. The evidence on the relation between uncertainty and bank lending is more recent and, crucially, it relies to date on aggregate or bank-level data only. Using consolidated data from the Call Reports, Baum *et al.* (2013) find that the evidence in support of the bank lending channel of monetary policy in the US becomes weaker after controlling for the volatility of the yields on one-year or five-year Treasury Bills, a

[3]If external financing is costly, these firms have a precautionary motive to reduce their debt and hoard cash in an uncertain environment, and this pushes them to scale down their investment more than unconstrained firms when uncertainty is high.

measure of financial risk. Valencia (2013) and Bordo *et al.* (2016) investigate the relation between the growth of bank lending and various measures of aggregate uncertainty for the USA (including disagreement among forecasters, stock price volatility and the Economic Policy Uncertainty index by Baker *et al.*, 2015), showing that uncertainty appears to discourage lending particularly for relatively less capitalized or illiquid banks, which provides indirect evidence of a causal impact of uncertainty on banks' lending policies. Raunig *et al.* (2014) reach a similar conclusion using an event study approach which focuses on lending dynamics around four uncertainty episodes, including the start of the Iraq war in 1990 or September 11th 2001. Alessandri and Panetta (2015) document that an increase in economic policy uncertainty predicts a tightening in the lending standards reported by European banks, as measured by the ECB's Bank Lending Survey. Gissler *et al.* (2016) introduce a specific measure of regulatory uncertainty exploiting the delays that occurred during the legislative process aimed at defining the new requirements for "qualified mortgages" in the US, and show that this correlates negatively with mortgage lending by US banks. Valencia (2016) documents a positive cross-sectional relation between the variance of banks' returns or capital buffers and their future capital ratios, consistent with the emergence of a self-insurance motive.

We share with some of these works the premise that bank capital is important to identify uncertainty effects. Since borrowing constraints effectively increase their risk aversion, weakly capitalized banks are likely to be not only less willing to lend, as known, but also more responsive to changes in the level of non-diversifiable risk in the economy. In other words, they should respond more to aggregate uncertainty shocks.[4] Our first contribution to the literature is to leverage on high-quality microeconomic data to test this possibility in a more stringent way than has hitherto been done. By studying within-firm outcomes, we can check how banks that differ in their capital buffers (and hence in their capacity to bear aggregate risk) treat credit applications submitted by the same firm at the same point in time, thus excluding a number of alternative mechanisms that might in principle generate analogous patterns in bank balance sheets or aggregate credit flows. In pursuing this avenue, we draw on the extensive empirical banking literature that has exploited loan applications and rejections to isolate credit supply from demand, using either official credit register data (Jimenéz *et al.*, 2012; Albertazzi *et al.*, 2016; Bonaccorsi di Patti and Sette, 2016; Ippolito *et al.*, 2016) or private banks' dataset (Puri *et al.,* 2011; Einav *et al.*, 2012; Dell'Ariccia *et al.*, 2012). In particular, we adapt the fixed effect saturation approach of Jimenéz *et al.* (2012, 2014) to study the heterogeneous impact of

[4]The relation between borrowing constraints, leverage and risk aversion is examined in Froot et al. (1993), Froot and Stein (1998) and more recently Rampini and Viswanathan (2010). Rampini et al. (2016) demontrate that equity also affects banks' risk management strategies and that well-capitalized banks are relatively more likely to hedge interest rate risk.

uncertainty across banks and firms. Our second contribution is to shed light on a dimension of bank lending – i.e. the time banks take to issue loans to their new borrowers – that has thus far been overlooked in the literature. Finally, we provide a first systematic analysis of how uncertainty and monetary policy interact in shaping banks' lending strategies.

3 The data

Our dataset combines various types of information. At the macro level, we use indicators of aggregate uncertainty, monetary policy and economic activity. At the micro level, we combine monthly loan-level observations on firms' credit applications with data on bank and firm balance sheets. We provide a brief description of the uncertainty indicators in Section 3.1 and discuss in detail the loan-level data in Section 3.2. More information on the remaining series and data construction details are provided in the Data annex. Throughout the analysis we follow Jimenez *et al.* (2014) in using the EONIA rate to capture the monetary policy stance. Using the one-month Euribor rate does not alter the results (see section 6). Importantly, no unconventional interventions took place in the euro area over our sample period, which runs from August 2003 to December 2012.

3.1 Uncertainty indicators

Our preferred indicator of aggregate uncertainty is the European *Economic Policy Uncertainty* index (hereafter EPU) constructed by Baker *et al.* (2015). The index is calculated counting the occurrences of uncertainty- and policy-related keywords in a set of daily European newspapers, and it aims to capture the uncertainty that surrounds monetary, fiscal and regulatory policy interventions in Europe. Policy and regulatory uncertainty are likely to be an important driver of bank lending strategies (Gissler *et al.* 2016). More generally, the EPU index has gained significant attention since its launch in 2012 and it has been used in a wide range of applied micro and macroeconomic empirical works on uncertainty.[5]

[5] A list of studies based on EPU indices maintained by the authors is available at http://www.policyuncertainty.com. The European EPU index combines information from ten newspapers, two for each of five countries (Germany, France, Italy, Spain and Great Britain). The Italian component of the index is also available separately, and our key results hold if uncertainty is measured with this indicator (see Section 4.1). Our choice to focus on the European index is based on three considerations. First, the Italian index is noisier: it is calculated using two papers only (Corriere Della Sera and La Repubblica), so it is more heavily affected by the idiosyncratic choices of a relatively small group of columnists and editors. Second, the key monetary, regulatory and fiscal policy debates that took place in 2002-2012 clearly had a strong international dimension. Third, three quarters of total banking assets in Italy are held by banks with branches or subsidiaries abroad (Caccavaio *et al.*, 2014), and these are likely to respond to uncertainty around the European rather than just the Italian outlook.

Since there is no commonly accepted way of measuring aggregate uncertainty, and most proxies are likely to be subject to measurement error, we consider for robustness a number of indicators that differ from EPU in terms of both conceptual grounding and empirical construction. The first one is the monthly average of the Euro STOXX 50 Volatility Index (VSTOXX), which measures the option-implied volatility on the Euro STOXX 50 equity price index over a 30 days horizon. Like VIX in the US, VSTOXX is a "fear" index that provides a market-based gauge of the volatility perceived by investors in the European stock market. The index is widely used as a proxy of aggregate risk perceptions in the euro area and it features regularly in official publications by the European Central Bank (see e.g. ECB Financial Stability Review, May 2014). A second alternative is *disagreement*, defined as the cross-sectional standard deviations of the forecasts issued by the professional forecasters surveyed by Consensus Economics®. We employ two disagreement indicators that are constructed using respectively forecasts on consumer price inflation and on the government budget balance in the euro zone.[6] As these choices make clear, our analysis focuses on the implications of aggregate rather than idiosyncratic uncertainty: the indicators are meant to pick up sources of uncertainty that relate to the overall state of economy and that might in principle affect all banks and firms at once, though not necessarily in the same way or to the same degree. The proxies we use might reflect both the level of actual risk in the economy and the agents' subjective or Knightian uncertainty about it. The difference between risk and uncertainty is conceptually interesting, but we do not see it as central to our work.

Figure 1 displays the behavior of the two EPU indices over our sample period. For comparison we also report VSTOXX. All indicators identify the first half of the sample as a relatively calm period: the end of the 2003 recession is followed by five years of mild and stable uncertainty. The Lehman crisis marks a clear regime shift. After 2008 uncertainty peaks again during the sovereign debt crisis in 2010 and 2011. The European EPU index is generally more persistent than VSTOXX and it reaches its historical maximum in 2011. The Italian version of the index follows a broadly similar pattern but it appears to be somewhat noisier, possibly on account of the smaller set of newspapers included in the calculation.

3.2 Loan applications and time to approval: stylized facts

We collect from the Italian Credit Register monthly information on all new loan applications advanced by a sample of 650.000 non-financial firms to Italian banks over the period between

[6] Inflation forecasts are useful because they summarize a large number of aggregate demand- and supply-side factors. The fiscal balance took center stage in the debate from the onset of the sovereign crisis. Ilut and Schneider (2014) use a disagreement indicator to estimate a general equilibrium model where Knightian uncertainty is a powerful driver of the business cycle.

August 2003 and December 2012. The sample includes firms from the manufacturing, industry, services and construction sector and it is broadly representative of the entire universe of capital companies. We only observe the applications placed to banks with which the borrower has no outstanding credit relation. As standard in the literature, we assign to each loan application a binary outcome ("approved" or "rejected") by inspecting whether, in the three months following its placement, the Credit Register records an increase in the credit granted to the enquiring firm by the bank that received the application. Of the almost 3 million of applications we observe, 2.3 were rejected, delivering an average approval rate of about 21%.

An overview of the behavior of applications and rejections over time is provided in Figures 2 and 3. Figure 2 shows the total number of applications along with the average number of applications per firm between 2003 and 2012. The latter is calculated by averaging over "active" firms, namely firms that submit at least one application in the month under examination, and gives an idea of the breadth and intensity of their loan search process.[7] The grey bars mark the two recessions that hit Italy over the sample period, as dated by the OECD. The main fact that stands out from the chart is the steady decline in applications from 2008 onwards, both at the aggregate and individual firm level. This is a clear sign that demand is an important driver of the patterns in the data. More specifically, the regression analysis must confront the possibility of a significant drop in demand after the Lehman crisis. A second interesting fact is that the number of applications does not systematically fall during recessions: both in 2009 and in 2011 there are distinct phases when the applications actually increase, albeit only temporarily. This raises interesting questions on the nature and motivations of the applicants: it might be for instance that recessions bring about 'lemon markets' where (otherwise inactive) bad borrowers crowd out good borrowers; or that, irrespective of their quality, firms shop around more in bad times to minimize the risk of ending up without loans. Our identification strategy, which relies on within-firm heterogeneity in the applications' outcomes, is designed to get around these problems. Since however these possibilities are interesting and worth investigating in their own right we discuss them in greater detail in Section 6.[8]

Figure 3 shows how the rejections line up against three survey-based measures of credit conditions. We consider the responses of Italian banks participating to the euro area Bank

[7]The median number of applications per firm is one (in other words, less than half of the firms submit multiple applications in any given month) and the distribution is highly skewed, with a standard deviation of 0.30 and a maximum of 6.98 over the full period. The occurrence of multiple simultaneous applications by the same firm is critical for identification: we discuss it further in section 4.

[8]A third evident fact in chart 2 is a strong seasonality in the data. In the econometric analysis we deal with it via seasonal dummies or, more radically, firm-month fixed effects.

Lending Survey (BLS) and two firm surveys conducted respectively by the Italian National Statistical Office (ISTAT) and the Bank of Italy in cooperation with IlSole24Ore. We focus on the 2008–2012 window only, for which all surveys are available. The series shows the net percentage of respondents –banks or firms, depending on the survey– that reported a perceived tightening in credit conditions in any given quarter. The monthly rejection series is averaged at the quarterly frequency to ease the comparison. Rejections track survey responses fairly well, both in general and in topical moments such as 2008/9 and 2011, when credit conditions are particularly tight. This illustrates why the Credit Register data is useful in isolating a credit supply channel. The decision (not) to grant new loans is an important component of a bank's overall strategy, and a timely signal of changes in its lending policy, but it is necessarily neglected when focusing only on observed variations in the outstanding stock of loans.

To study the timing of banks' decision we resort to a second binary variable, $Postponed_{fbt}$. This is created by (i) restricting the sample to the applications that were eventually approved, and (ii) inspecting whether the corresponding loans were issued in the month following the request (in which case the dummy is equal to zero) or with a delay of two or three months (dummy equal to one). Since one month is the shortest horizon over which new loans can appear in the data, the dummy sets aside all applications that were "postponed" rather than being approved straightaway. The rationale behind this variables is simple: a rise in uncertainty could induce banks to take more time before giving out a loan (besides rejecting more applicants), either because they wait for new or better signals on the state of the economy or because they try to collect more information on the quality of the applicant. This test is also useful from an identification perspective. By restricting the analysis to successful applications only, we focus on good borrowers and good projects, which limits concerns on changes in the composition of applications over time. In other words, with this variable we effectively rely on the banks themselves (and on some hindsight) to get around the possibility that the pool of projects may systematically worsen in bad times, which could lead to a spurious negative correlation between the approval rate and uncertainty.

The applications are accepted on average after 1.4 months, with a standard deviation of 0.6 months. The timing of the approvals displays an interesting behavior at the aggregate level. The share of postponed applications over total approvals is positively correlated with all our uncertainty indicators. Some of them, including EPU, also have significant predictive power for this ratio. In the case of the EONIA rate, on the other hand, the correlation is weak and predictability runs in the opposite direction (see table A1 in the annex for details). This provides *prima facie* evidence that the timing of the approvals is influenced specifically by the level of uncertainty in the economy.

4 Uncertainty and loan approvals

4.1 Is there a credit supply channel?

The primary objective of our analysis is to establish whether *ceteris paribus* banks reject more loan applications when economic uncertainty is high. A second and closely related objective is to test whether they also become less responsive to monetary policy: fluctuations in interest rates may matter less in highly uncertain environments. To this dual end, we estimate a set of models where the dependent variable is a dummy $Approval_{fbt}$, which takes value 1 if the credit request advanced by firm f in month t to bank b is approved within three months and zero otherwise (as in Jiménez *et al.*, 2014), the key regressor is the EPU uncertainty index by Baker *et al.* (2015), and the potential influence of uncertainty on the transmission of monetary policy is captured by an interaction between EPU and the EONIA rate.

Our loan-level data allows us to estimate regressions that include firm-specific fixed effects that vary at the monthly frequency (Jimenéz *et al.* 2014). These present clear advantages in terms of identification: the firm-month effects capture all changes in business cycle conditions and firm characteristics that may influence the demand for credit, thus allowing a reliable estimate of the impact of uncertainty on the supply side of the credit market. Confining the analysis to such a set up, however, would be limiting: the relation between uncertainty and the average approval rate (which is absorbed by the firm-month fixed effects) is interesting in its own right, and the cross-sectional results are harder to interpret without some prior knowledge about this average effect. To fully exploit our data we thus proceed sequentially. We start from relatively rudimentary regressions that only include macroeconomic and bank-specific controls and then progressively move towards saturated specifications that include firm-month fixed effects. An important element of our identification strategy is to exploit heterogeneity in banks' capital buffers as a proxy of their risk-bearing capacity and hence of their sensitivity to uncertainty. The progression towards increasingly rich specifications allows us to thoroughly test this mechanism and check whether the role of capital changes when tightening the controls for credit demand.[9]

table 1 about here

[9] In Section 4.2 we study alternative specifications that include both *firm-month* and *bank-month* fixed effects to assess the influence of uncertainty on the composition of credit.

The estimates are displayed in Table 1. In the first column loan approvals are regressed exclusively on the EPU index, a set of macroeconomic and bank-specific control variables and the firms' credit ratings. The macro controls include CPI inflation, industrial production growth and unemployment in Italy, all lagged one period. The bank controls are the Tier 1 capital ratio, the liquidity ratio, and two dummies that identify respectively mutual banks (small-scale lenders that mostly operate at a local level) and the five largest banks in the sample (more complex and diversified institution with a national or international dimension). Controlling for credit ratings is important as a good rating may (and in fact turns out to) systematically improve an applicant's chance of being approved. These regressors are included in all subsequent specifications. This initial regression returns a negative and highly significant EPU coefficient, providing prima facie evidence that the approval probability drops when uncertainty rises.[10]

In column 2 we introduce the EONIA rate, both in isolation and interacted with EPU, leaving the rest of the specification unchanged. EPU retains its significance. The negative and significant coefficient of EONIA is in line with the extant literature on the bank lending channel, that provides ample evidence that a tightening in monetary conditions leads to a decline in the supply of credit. The interaction between EPU and EONIA is positive and highly significant: *ceteris paribus,* high uncertainty weakens the influence of monetary policy on loan approvals. This result demonstrates that, when faced with changes in economic conditions in uncertain times, banks adopt a wait-and-see behavior analogous to that of nonfinancial firms (Bloom, 2007, 2014). It also offers one explanation why monetary policy might be relatively less effective when the economy is in recession and volatility is high (Tenreyro and Twhaites, 2016). The estimates suggests that the impact of uncertainty on loan approvals is quantitatively in the same ballpark as that associated to monetary policy itself. To put the estimates in context, note that the EONIA rate is expressed in decimal points while EPU is normalized to 1 in 2000 and has a standard deviation of 0.53. Given this scaling, the coefficients in column 2 imply that, starting from the current 'zero lower bound' on interest rates, a 100 basis points rise in EONIA would lower the approval probability by 1.1% and a one standard deviation increase in EPU would lower it by 2.1%.

The next step is to bring bank capital into the picture. The influence of uncertainty should be stronger for banks that have low capital buffers and hence less capacity for holding aggregate risk. We investigate this possibility by interacting the banks' Tier 1 capital ratio with the EPU terms. Since capital is known to matter for the transmission of monetary policy too, we

[10] Errors are clustered at the bank*month level troughout the paper, following Jimenez *et al.* (2012). When we saturate the model with bank*month and firm*month fixed effects we restort to a triple cluster (bank, firm and month). In general, results are robust to alternative clustering, including by month and by bank and month.

also include its interaction with EONIA.[11] The test is performed in three alternative set-ups: in column 3 we simply add the capital-based interactions to the specification of column 2; in column 4 we augment the regression with bank and firm fixed effects; and in column 5 we saturate it with a full set of firm-month fixed effects. The upshot from this exercise is that capital has a powerful dampening effect for uncertainty shocks. This mechanism involves both the direct and the indirect effect of uncertaunty: higher capital makes banks both less responsive to variations in EPU and less prone to adopting a wait-and-see type of behavior. These patterns appear consistently across specifications 3 to 5. Column 5 is of course of particular interest. Owing to the presence of firm-month fixed effects, a confusion between demand and supply channels is in this case extremely unlikely. The level effects of EPU and EONIA are absorbed by the fixed effects and the sample size drops by an order of 10 because the estimation relies exclusively on firms that apply to more than one bank in any given month. In practice this model checks how the propensity to approve applications coming from the same firm in the same month changes across banks depending on their capital ratios. Conditional on a rise in uncertainty, the approval rate drops significantly less for highly capitalized banks. The coefficients in column 5 can be used to quantify the importance of capital. The median capital ratio in our sample is 8.7%. Relative to that benchmark, a one standard deviation rise in EPU causes the approval probability to drop 0.3 percentage points more for banks with a 6.1% capital ratio (the lowest decile of the distribution) and 0.7 percentage points less for banks with 15.5% capital ratio (the highest decile). Note that both the average effects of EPU and EONIA (columns 1 to 4) and the dampening role of capital (columns 3 to 5) turn out to be very robust across models.

In table 2 we replicate the analysis using alternative indicators of economic uncertainty. In panel (a) the European EPU index is replaced first by VSTOXX (columns 1 to 4) and then by the Italian EPU (columns 5 to 8). In panel (b) we use forecasters' disagreement on CPI inflation (columns 1 to 4) and the public budget balance of the euro area (columns 5 to 8). For each of the indicators we estimate the same models used in Table 1, replicating the progression from a specification with bank and macroeconomic controls to a fully saturated regression with firm-month fixed effects. The key results of our analysis are remarkably robust. In all combinations of proxies and specifications we estimate a negative coefficient for uncertainty and a positive coefficient for the interaction between uncertainty and EONIA. In the saturated regressions, the dampening effect of bank capital appears for three indicators out of four, the exception being VSTOXX. This suggests that measurement problems are extremely unlikely to constitute

[11] As we noted above the capital ratio is included as a control variable in all regressions of table 1. Not surprisingly its coefficient is positive and significant in most cases, suggesting that well-capitalized banks are on average more willing to accept new customers.

a first-order problem in our analysis (we discuss measurement problem more in section 6).

table 2 about here

Another important concern is the stability of the estimates over time. Economic conditions changed significantly between 2003 and 2012, as the Italian economy transitioned from a relatively calm phase, with constant or rising interest rates, to two crisis episodes – the global financial crisis of 2008-2009 and the subsequent sovereign debt crisis – that were accompanied by significant monetary expansions. To check how the transmission of uncertainty changed in these periods we re-estimate the saturated specification in column 5 of table 1 separately for each year of the sample. The estimated coefficients are displayed in figure 4. The figure reports the point estimate and a 90% confidence interval for each of the three interactions involving bank capital. The estimates are generally larger and less accurate in the second half of the sample, but the signs of the coefficients are extremely robust. In particular, the interaction between capital and EPU always enters the regression with a positive coefficient except in 2005, when it is approximately zero. The significance levels of the estimates are also surprisingly high considering that each of these year-specific regressions only relies on 12 observations on EPU and on an overall sample size of approximately 250,000 observations due to the fixed effect saturation.

In Section 6 we examine the robustness of the results in table 1 along various other dimensions and discuss a range of microeconomic phenomena that might in principle interfere with our identification strategy, including changes in the quality and composition of the applications or in their distribution across banks. In the remainder of this section we investigate instead how the transmission of uncertainty changes depending on banks' liquidity, size and business model. Like capital, liquidity might in principle dampen banks' reaction to aggregate uncertainty. Liquidity is unlikely to directly affect a bank's attitude towards credit risk, but it might for instance increase its tolerance for maturity risk, making it more willing to commit its funds for longer time periods. Banks' size and business models are also likely to play some role, as small local lenders and international players are unlikely to deal with uncertainty (or even perceive it) in the same way. To explore these possibilities, in table 3 we re-estimate the regressions interacting uncertainty with liquidity, size or business model indicators instead of the banks' capital ratios. The exercise is performed for both the regression based on bank and firm fixed effects (where EPU and EONIA appear independently) and the saturated specification with firm-month fixed effects (where they only appear through their interaction with the relevant bank indicator).

table 3 about here

We find that liquidity plays a role in dampening the transmission of both monetary policy and uncertainty. Interestingly, in the latter case liquidity works mainly by reducing banks' inaction region: this implies that liquid banks respond less on average to monetary shocks, as demonstrated by the bank lending channel literature, but their response is also more stable, i.e. less dependent on the prevailing level of uncertainty. While large intermediaries do no appear to behave differently from the average bank, mutual banks display a lower-than-average sensitivity to uncertainty (column 6). This may indicate that they are less informed, or that their business model leads them to pay less attention to the aggregate, economy-wide risks captured by the EPU index.[12] In section 4.2 we explore heterogeneity across applicants in order to discriminate between these mechanisms.

4.2 The composition effects of uncertainty

Our loan-level dataset makes it possible to push the saturation of the model one step further and introduce *bank*month* fixed effects alongside the $firm^{*}month$ effects used in the previous section. A similar exercise is proposed in a different context by Jimenez *et al.* (2012, 2014). In this set up the interaction between uncertainty and bank capital is also absorbed by the fixed effects and the analysis must focus on triple interaction terms where uncertainty is combined with both bank and firm characteristics. This specification follows a different logic than those pursued in Section 4.1. In this case the objective is not to refine the identification of the supply-side effects of uncertainty, but rather to draw a more detailed picture of its compositional implications: which bank-firm relations are most affected by uncertainty? And what are the features of the 'marginal borrowers' that get rejected in uncertain times?

Table 4 reports the results of a range of "fully saturated" specifications that include both bank- and firm-level monthly fixed effects. For each specification we report the estimated coefficients for the triple interactions between EONIA or EPU and some combination of bank and firm characteristics. The specifications only differ because of these combinations. On the bank side, following the analysis in the previous section we consider the capital ratio (panel (a), columns 1 to 3), the liquidity ratio (panel a, columns 4 to 6) and two dummies that identify mutual banks (panel b, columns 1 to 3) and the five largest banks in our sample (panel b, columns 4-6). On the firm side, we condition on the new potential borrowers being large (assets above the 90th percentile of the distribution), having a good credit rating (Altman's *et. al.* (1994) z-score below 3, where 1 is assigned to the best borrower and 9 to the worst ones) or being headquartered in the

[12] Mutual banks appear less sensitive even if we use the Italian EPU index instead of the European one, dispelling any concerns that the latter might simply measure uncertainty at the wrong geographical level (the results are available upon request).

same province as the bank they apply to. Since in these models the estimation relies exclusively on banks and firms that engage in multiple relation at any given point in time, the size of the sample drops considerably relative to Table 1.[13]

table 4 about here

The dampening role of bank capital emerges again consistently in columns 1 and 3 of panel a. This provides an important validation of the results discussed in Section 4.1. Although they do not change the basic message, these estimates show that capital remains important for the transmission of uncertainty even if one controls for the observed and unobserved factors that affect the average behavior of each bank at a given point in time. Notably, such factors include the banks' (time-varying and potentially idiosyncratic) views on both the path of future economic activity and the real state of their balance sheets, which are unlikely to be captured by balance sheet data.

Liquidity reduces the transmission of uncertainty to local borrowers (on which see below) but not to large firms. Highly liquid banks are in fact *less* likely to accept these as new customers when uncertainty is high, possibly on account of a bad match between their own preferences for holding liquid securities and the clients' needs (large loans attached to complex investment projects). The comparison between mutual banks and large banks is also informative. These banks behave roughly in the same way when dealing with large or highly rated firms. The only factor that really sets them apart is their attitude towards local firms: mutual banks have much higher approval rates for firms that are located in their own province (panel b, column 3), whereas geographical proximity is completely irrelevant for large banks (column 6). The emergence of a positive role for physical proximity is coherent with the literature on distance, monitoring and credit supply (see Degryse *et al.* 2007 for a survey). In our case, the findings shed some light on the reasons why small lenders are less responsive to uncertainty. Given that their approval rates drop for the average borrower more than the local ones, their behavior cannot be driven by lack of information on the state of the economy. The discrimination suggests instead that local borrowers are preferable from their perspective when uncertainty is high, either because gathering information about them is easier or less costly or because their projects have a high 'alpha' but a low 'beta' (i.e. they carry significant *idiosyncratic* risk but are less correlated with the *aggregate* risks captured by the EPU indicator). What is also interesting, and perhaps somewhat puzzling, is that distance matters more than firms' credit ratings: in table 4 the 'same province' dummy is

[13] Errors are here clustered at the bank, firm and month level, following Jimenez *et al.* (2014). Note that the number of observation changes across columns because it also depends on the availability of bank-level data.

positive in three cases out of four (when interacted with capital, liquidity, and the mutual bank status) while the rating dummy is never significant. From a firm's perspective, geographical proximity is thus a far better hedge against uncertainty shocks than a sound credit record.

5 Uncertainty and the timing of loan approvals

Uncertainty could also affect the timing of the approvals: obtaining a loan may take longer when uncertainty is high. To test this proposition we separate firms' applications depending on how quickly they got approved and then check if the likelihood of a longer approval process rises systematically after an increase in uncertainty. More specifically, we restrict the analysis to the subsample of applications that were ultimately successful (i.e. those for which $Approval_{fbt} = 1$), and define in this set a dummy $Postponed_{fbt}$ that takes value zero for the applications that were approved within a month following the submission and value one for those that were instead "postponed" and incurred a delay of one month or more.[14] Besides being interesting in its own right, this variable is valuable from an identification perspective. In some of the regressions examined in Section 4.1, failure to fully capture banks' expectations on the economy might mean that bad news (that are typically associated with a rise in EPU) may bias our estimate of the uncertainty coefficient.[15] This should be less of an issue with $Postponed_{fbt}$ because the natural response to outright bad news is to reject more applications, not to postpone the decisions. More importantly, by restricting the analysis to successful applicants we focus on good projects only and hence limit any concerns one might have on how the composition of the applications changes over time. This variable effectively allows us to rely on the banks themselves to rule out the possibility that the pool of projects in the estimation sample worsens in bad times, leading spuriously associate drops in the approval rate to uncertainty.[16]

table 6 here

A set of loan-level regressions of $Postponed_{fbt}$ on EPU are reported in Table 5. Since we have no priors on whether the timing of banks' decisions should respond to the level or to the

[14] In principle one could estimate a multivariate logit model including all approval dates ($t+1$, $t+2$, $t+3$) as alternative outcomes. Since however our objective is to test the null hypothesis that uncertainty does not influence the approval timing at all, a linear model based on a binary dummy is valid and simpler alternative to it.

[15] We emphasize however that this problem cannot arise in the models of Section 4.2, where the bank-month fixed effects also capture banks' (potentially heterogeneous) expectations on the macroeconomic outlook.

[16] The saturated regressions in Section 4 already control for changes in the composition of the pool of *firms* via firm-month effects. Here we go one step further and try to fix selection problems at the level of *projects* (i.e. applications) too.

variation in uncertainty we provide results based on both specifications. We again build up the specifications going progressively from plain OLS regressions (columns 1 and 4) to regressions that include bank and firm fixed effects (columns 3 and 6), including in all cases the usual set of controls. The coefficient is positive and significant across specifications, implying that the likelihood of an application being postponed increases systematically when uncertainty is high or on the rise. Interestingly, $Postponed_{fbt}$ is not correlated to levels and changes in the EONIA rate (see table A2 in the annex). Given that EONIA contains information on the current and expected state of the economy, but not on the uncertainty that surrounds them, its lack of significance confirms that these regressions isolate a genuine uncertainty effect. The delays are associated with the banks' difficulty in forming forecasts on the future path of the economy rather than with (downward) revisions in those forecasts.

Additional regressions reported in the annex to the paper confirm that this relation is robust across uncertainty indicators (tables A3), and show that it varies across firm (but not bank) characteristics (table A4). In particular, firms that are located close to the bank to which they place the application face a probability of being postponed that is low on average but rises relatively more in response to an increase in uncertainty. Combined with the results of section 4.2, this suggests that, although proximity is a good hedge against uncertainty-driven rejections, local applicants are kept on hold for longer when uncertainty rises, possibly because banks exploit some degree of informational hold-up power on close-by firm (Diamond, 1991). A similar pattern emerges indeed for firms that are below the 90^{th} percentile of the total asset distribution.

6 Discussion

In this section we examine briefly a range of additional robustness tests and then discuss alternative mechanisms that might in principle give place to the patterns we observe in our data. The estimates of the level effect of uncertainty on the average approval rate displayed in column 2 of table 1 keep their sign and significance when including bank and firm fixed effects, irrespective of how uncertainty is measured (see table A5 and A6 in the annex). Since EONIA and our main uncertainty proxies are defined at the European level, and are consequently not driven by economic conditions in Italy, endogeneity with respect to the Italian business cycle is unlikely to be a serious problem. At any rate, using lags of these variables in the regression, either in combination with or instead of their contemporaneous values, leaves the estimates essentially unchanged (table A5, columns 1 and 2).

Another set of problems relates to measurement, at both the macroeconomic and microeconomic level. To check the potential mismeasurement of monetary policy we replace EONIA with the one-month EURIBOR rate (table A7, column 3). Since EPU might conceivably pick up the effect of plain bad news about the future of the economy, as well as genuine uncertainty, we also add to the regression two survey-based measures of expectations. In particular, we use the Economic Sentiment Indicator for Italy (a broad indicator that combines consumer and firm information) and a measure of Italian firms' expectations on production, employment and selling prices over the following 12 months constructed using the surveys run by the European Commission. The results are again in line with the baseline (table A7, column 4). The EPU coefficients are actually larger than those estimated in our baseline regression, suggesting that the uncertainty indicator is not inflated by the occurrence of bad news.[17]

Measurement issues may also involve the loan application data. The reporting threshold in the Credit Register was lowered in 2009 from 75,000 to 30,000 euros, resulting in an increase in the number of loans traceable in the records. This change is of course irrelevant for the regressions that include *firm*month* fixed effects, or are estimated separately year by year (see Section 4.1), but it must be dealt with in all other cases. To bypass the break, in our analysis we consider only loans above 75,000 euros throughout the sample (as in Bonaccorsi di Patti and Sette, 2012). As a further robustness we estimate the model using only large firms (those with assets above 90^{th} percentile of the distribution), which are virtually unaffected by the change, or relying on the raw, unadjusted data. Our main conclusion hold in both cases (see table A7, columns 5 and 6). During the period we consider the banking sector underwent a number of mergers and acquisitions. In principle M&As should not affect our dependent variable, as this only covers new requests for credit. However, when assessing the existing credit relations of the acquired bank(s), the acquirer might possibly place for convenience queries to the Credit Register which appear as new applications in the data. If M&A activity were to concentrate in periods of low uncertainty, this could create a negative correlation between uncertainty and the probability of approval. For this reason in our baseline analysis we exclude from the sample all queries advanced by newly formed groups in the year when the M&A takes place. Including these observations, however, does not affect the results (table A7, column 7). Finally, the applications display strong seasonal patterns, with regular falls in August and December (see Figure 2). To account for this, we include in the model a full set of month dummies: the impact on the coefficients of interest is again negligible (table A7, column 8).

Going beyond robustness, the credibility of our results can also be scrutinized from a broader

[17] In table A8 we present the result of the two robustness tests that we can carry out on the specification with the interaction with capital (columns 4 and 5 table 1), i.e. swapping the coefficients with their lagged values and substituing EONIA with euribor. Results are robust.

economic perspective. Our findings could in principle also be explained by changes in the composition of the applicants over time: if the pool of applicants deteriorates during downturns, we might wrongly link to uncertainty an increase in the rejection rate that depends instead on the declining quality of the borrowers. Surprisingly, though, the borrowers do not get worse in recessions. In Figure 5 we plot the average credit rating of the applicants over time. Lower numbers are associated to better borrowers, with 1 representing the highest credit quality. The chart shows that the average rating improves after Lehman, suggesting a self-selection process on the firms' side that should -if anything- run against our results. Another interesting fact is that this qualitative improvement is even more visible in the case of successful (i.e. approved) borrowers: the average ratings of applicants and successful applicants overlap in the first half of the sample but a clear gap opens up between them after 2008, indicating a stronger selection on the banks' side too. This might of course represent yet another adjustment of the lenders to a riskier environment. In any case, these dynamics are fully controlled for at the firm level by the firm-month fixed effects. Furthermore, our analysis of the timing of banks' decisions in Section 5 is not affected by credit quality concerns even at the project level, as it focuses only on applications that are eventually approved by the banks.

Another possibility is that our results are partly driven by a "congestion" problem. If they systematically get more applications in bad times, banks could become more willing to reject marginal applicants and slower at processing the applications, leading at once to an increase in rejections and a lenghtening of the waiting time for successful firms. In aggregate terms, the number of applications generally declines rather than increasing in the highly uncertain years that follow the Lehman crisis (see Figure 1 and 2). There are however episodes when the applications do increase – for instance in the middle of the 2009 recession – and in any case the aggregate pattern might mask heterogeneity in their distribution across banks. To shed more light on this possibility we look at the average number of application received per month by different bank categories. This is roughly constant for all bank categories, with the exception of a short-lived increase in the applications submitted to 'large' banks in the first half of 2011 (see figure A1 in the annex). Re-estimating our *Postpone* regression without these observations leaves the results unaffected, confirming that the congestion explanation can be safely ruled out (the results are available upon request).

7 Conclusions

Credit systematically dries up when the future is uncertain. The theory suggests that this phenomenon might reflect both demand dynamics – uncertain firms are more likely to postpone their investment decisions – and supply-side effects, as lenders are less willing to finance new projects when their returns become more volatile. In this article we exploit confidential loan-level data from the Italian Credit Register to test the existence and the scope of the second transmission mechanism. We study the outcome of loan applications submitted to Italian banks by a large sample of firms between 2003 and 2012. To isolate the impact of uncertainty on the supply of credit we exploit the occurrence of multiple bank-firm relations and compare the outcomes of applications placed in the same time period by the same firm to banks that have different capital buffers, and hence a different propensity to hold aggregate risk.

Our conclusion is that the credit market is all but a sideshow to the propagation of uncertainty shocks. We obtain three main results. First, a rise in aggregate uncertainty lowers the likelihood that firms' applications will be successful, reducing the supply of new credit. Second, uncertainty delays the flow of funds to the economy: even successful applicants must wait longer for their loans to be issued when uncertainty is high. Third, uncertainty interferes with the bank lending channel of monetary policy. When uncertainty is high banks become less sensitive to changes in interest rates, displaying a *wait-and-see* behavior that is entirely analogous to that traditionally documented for nonfinancial firms. Uncertainty matters relatively more for thinly capitalized banks, as predicted by the theory, and it is more likely to affect firms that are geographically distant from the bank to which they apply.

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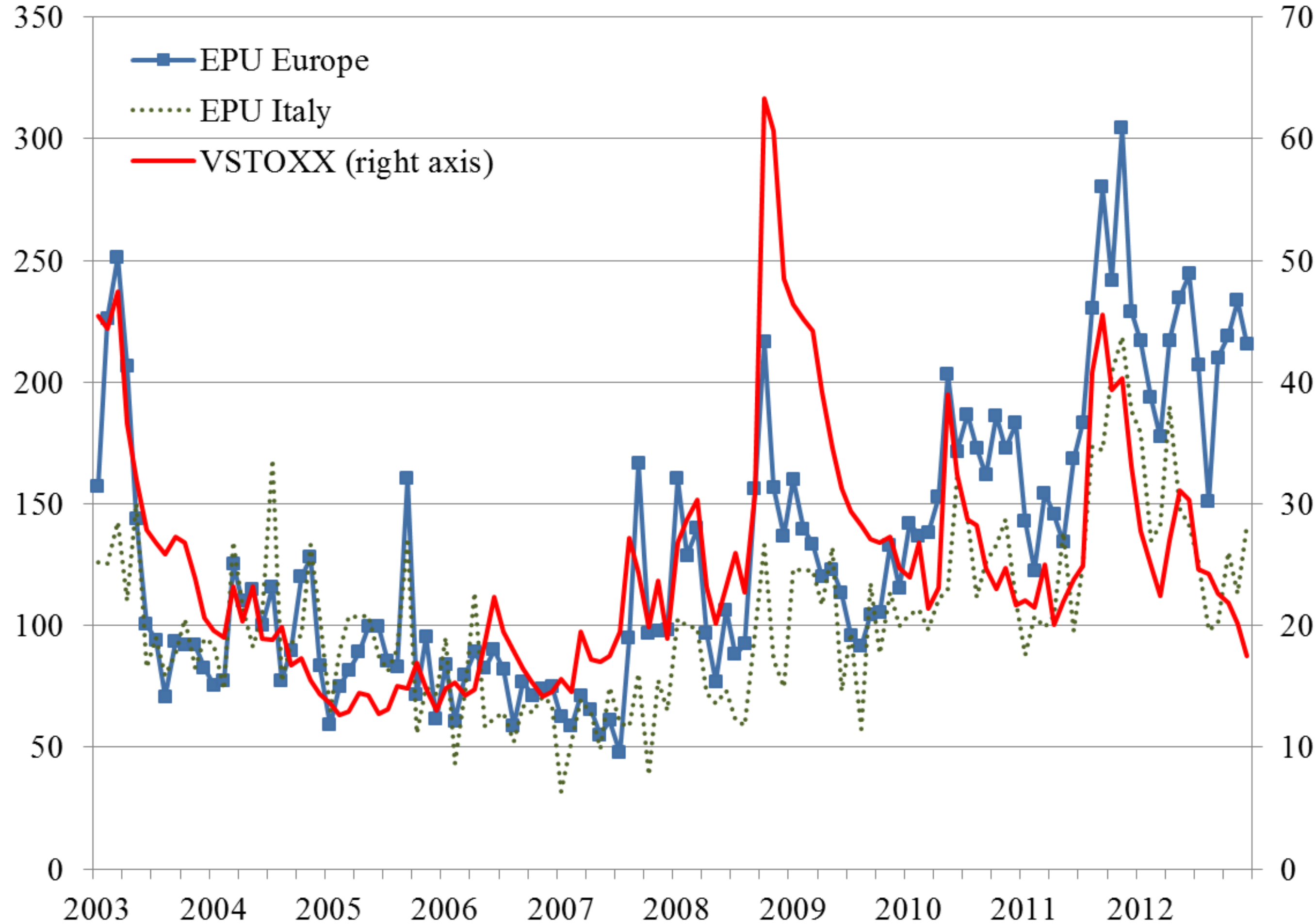
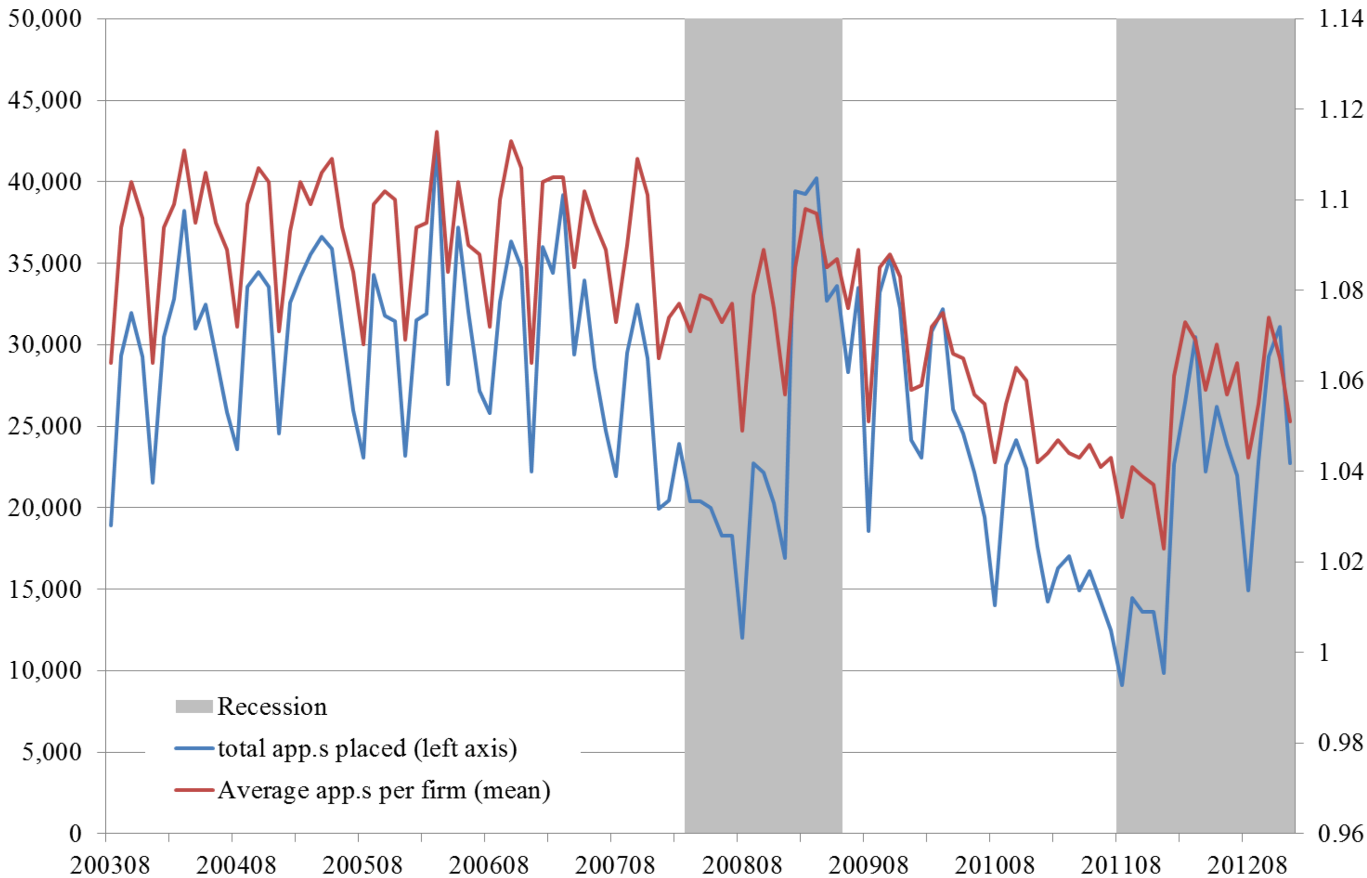
Figures

Figure 1. Uncertainty indicators over time



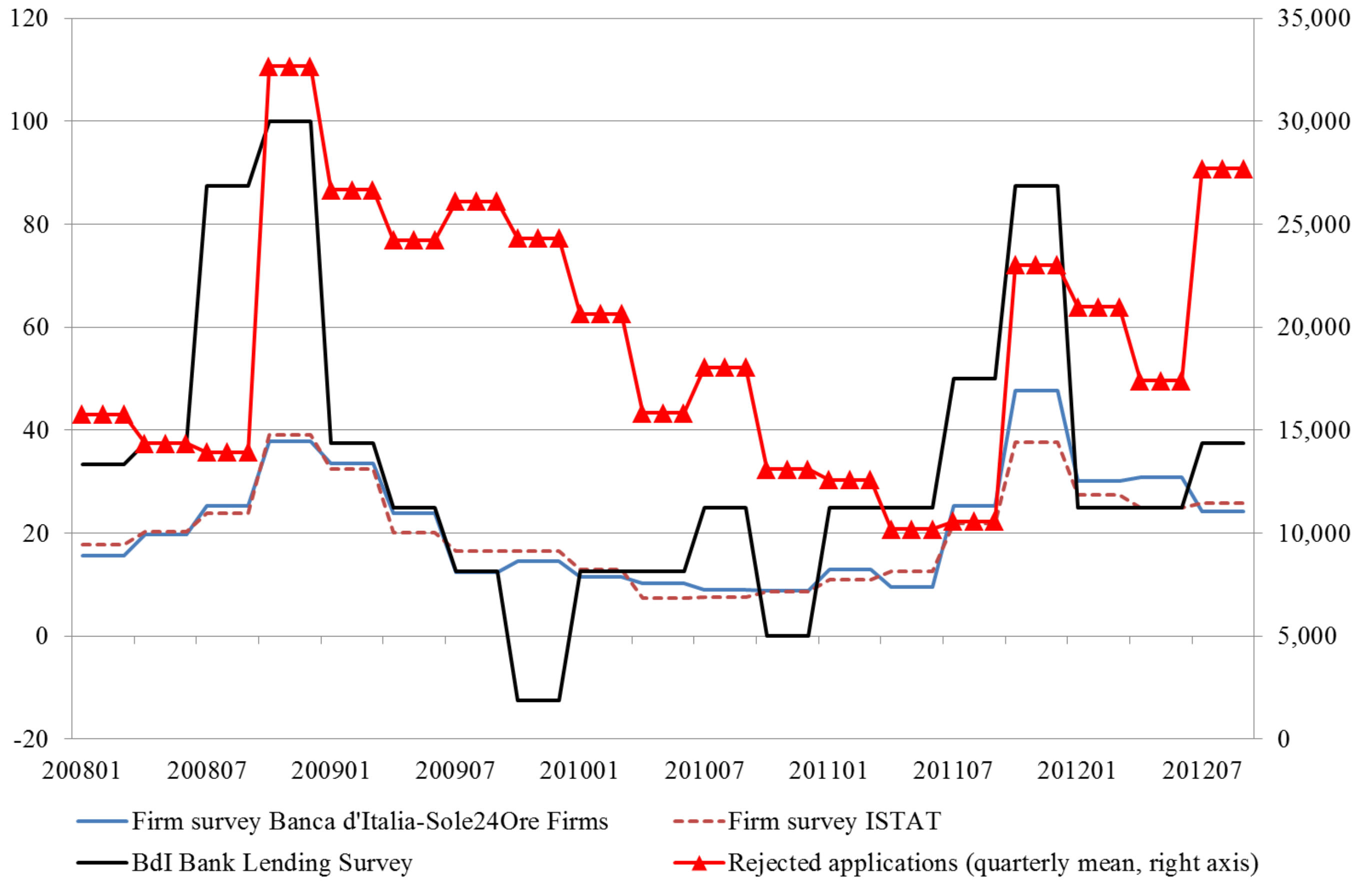
Note: Note: VSTOXX (left scale) is the monthly average of the daily VSTOXX stock price option-implied volatility index. EPU (right scale) is the Economic Policy Uncertainty indicators constructed by Baker et al. (2015) using the frequency of uncertainty-related keywords occurring in a set of European and Italian daily newspapers. Sources: Datastream and www.policyuncertainty.com.

Figure 2. Loan applications



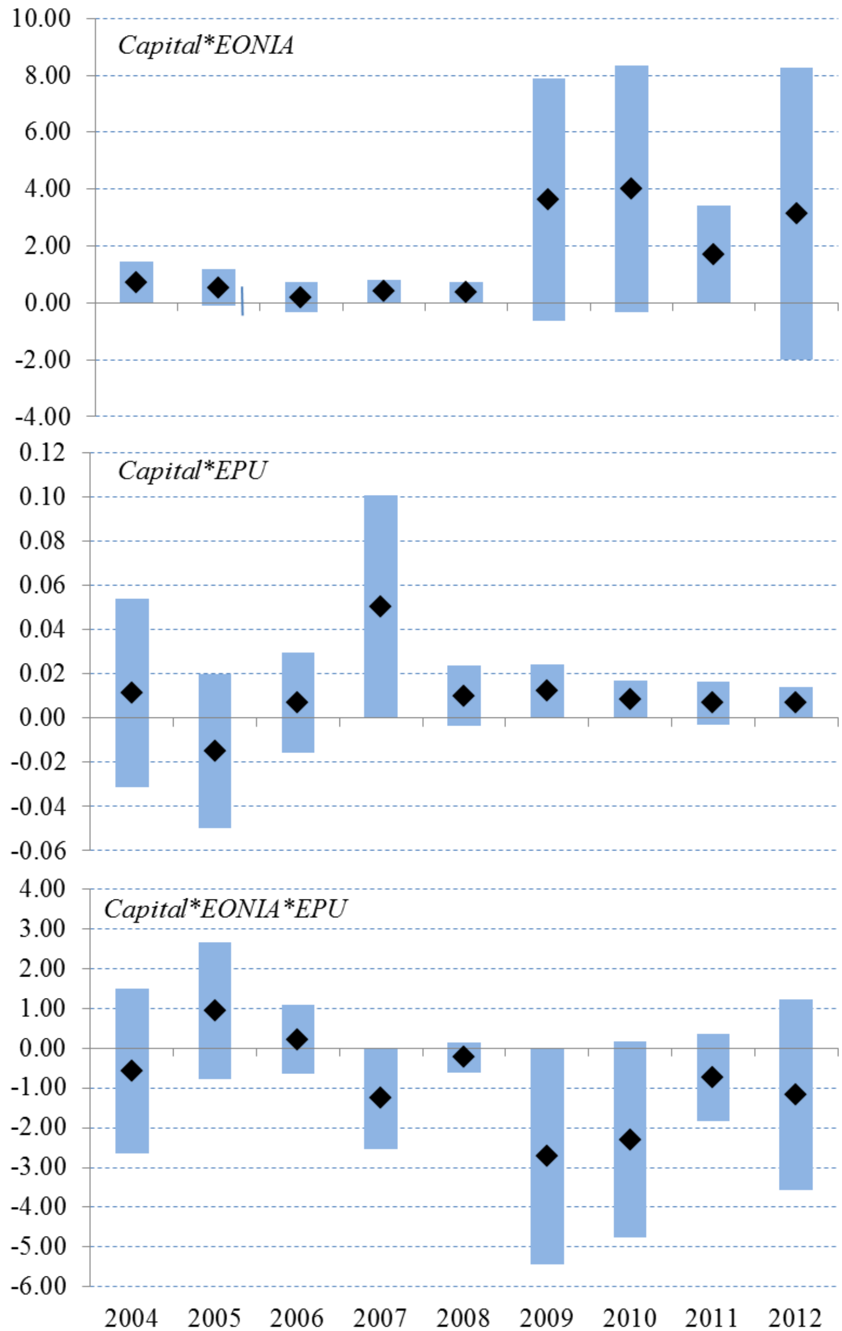
Note: The blue line shows the total number of loan applications placed by firms (left scale). The red line shows the average number of applications placed by firms who submitted at least one application (right scale). Grey bars identify the recessions dated by the OECD. The sample period is August 2003 – December 2012. Source: Italian Credit Register and authors' calculations.

Figure 3. A comparison between rejections and survey responses



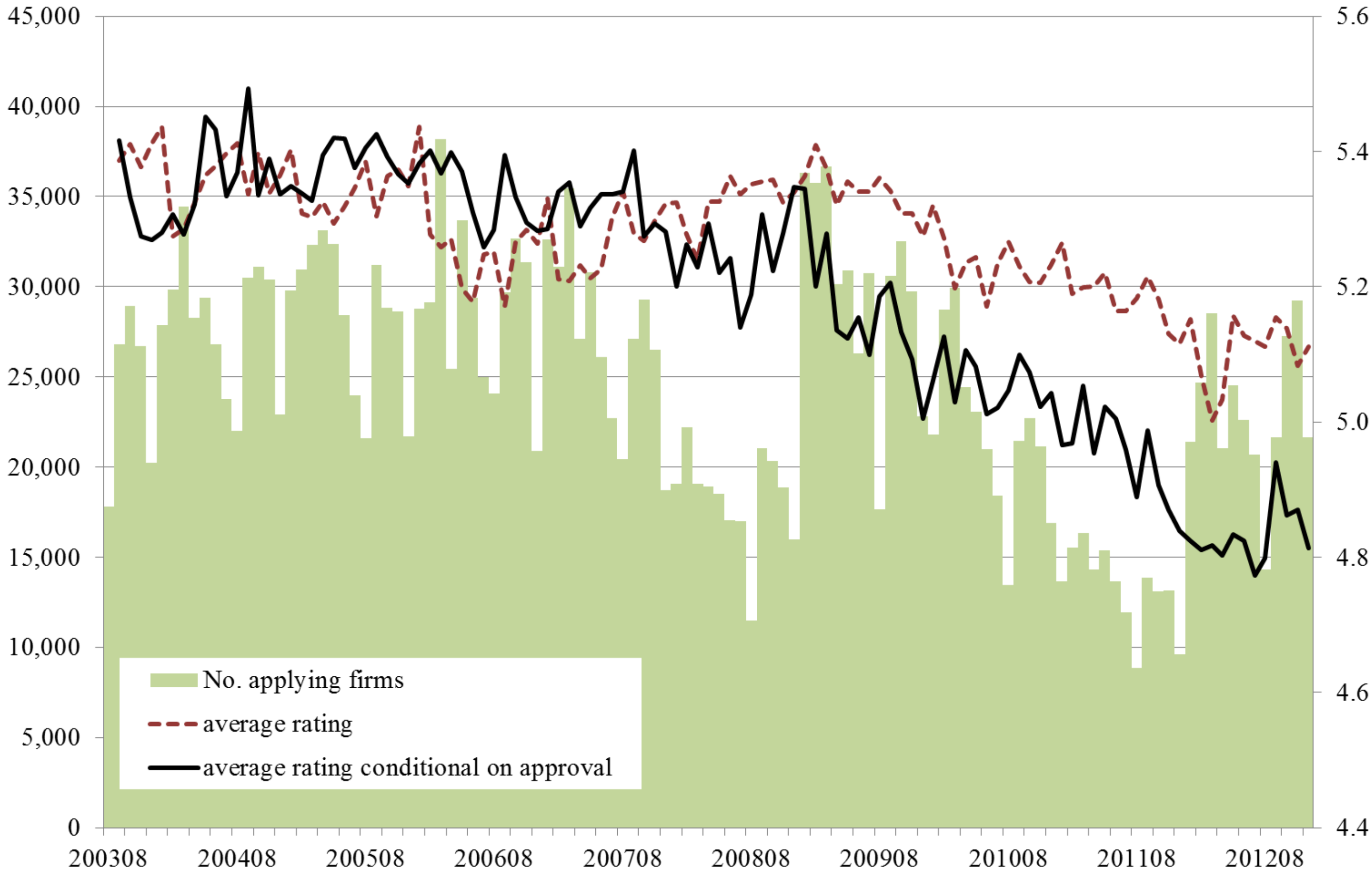
Note: The lines shows the quarterly mean of applications placed against a number of survey indicators of credit supply conditions in Italy. The black line is the net percentage of the responses of Italian banks participating in the euro area bank lending survey that indicate a tightening in credit standards and those indicating a loosening, compared with the previous quarter (increases indicate that credit supply have been tightened). The blue line is the net percentage of firms surveyed in the Bank of Italy-Il Sole24Ore survey that indicate to have perceived a restiction in credit supply. This is conducted quarterly on a sample of medium-sized and large firms (with at least 50 employees) in industry (excluding construction) and services. The dotted line is ditto for the Istat business confidence surveys are conducted on samples of manufacturing and service firms (excluding retail and wholesale trade) and construction companies. Source: Italian CredRegister, ISTAT, Bank Lending survey and authors' calculation.

Figure 4. Parameter stability.



Note: The chart present the resutl of a robustness test assessing the stability of the findings acroos the sample period. The panels report the point estimates and a 90% confidence interval for each of the three interaction terms. Estimation is based on a regression model where the dependent variable is the loan approval probability and the controls include the interaction between bank capital and EONIA, the interaction between bank capital and the EPU index, a triple interaction between capital, EONIA and EPU and a full set of firm-month fixed effects (see table 1, column 5). The regression is estimated separately for each year between 2004 and 2012.

Figure 5. Number and credit quality of the applicants.



Note: Green bars indicate the number of firms that submitted loan applications in any given month (left axis). The red dashed line shows the average credit rating of the applicants (right axis) and the black continuous line shows the average credit rating of those whose applications were approved (right axis). Credit ratings are calculated by Cerved and range from 1 to 9, with 1 denoting the best firms. Source: Bank of Italy Credit Register and authors' calculations

Tables

Table 1. The impact of uncertainty on loan approval

	approval				
	(1)	(2)	(3)	(4)	(5)
EPU EU	-0.023***	-0.039***	-0.061***	-0.062***	
	(0.003)	(0.006)	(0.011)	(0.007)	
eonia		-1.133**	-1.483*	-2.609***	
		(0.486)	(0.816)	(0.427)	
EPU EU*eonia		1.753***	2.713***	2.820***	
		(0.329)	(0.578)	(0.361)	
capital*EPU			0.002**	0.001	0.002*
			(0.001)	(0.001)	(0.001)
capital*eonia			0.019	0.102***	0.114**
			(0.049)	(0.034)	(0.055)
capital*EPU*eonia			-0.078**	-0.069***	-0.067*
			(0.035)	(0.026)	(0.038)
bank controls	yes	yes	yes	yes	yes
firm rating	yes	yes	yes	yes	-
macro controls	yes	yes	yes	yes	-
bank FE	no	no	no	yes	yes
firm FE	no	no	no	yes	-
firm*month FE	no	no	no	no	yes
observations	2259892	2259892	2259892	2078492	260390
estimation	OLS	OLS	panel FE	panel FE	panel FE

Note: these regressions examine the effect of an increase in uncertainty on the probability that an application is approved, considering the transmission via bank capital. The dependent variable is *approval*, taking value 1 if the loan application is approved. *EPU EU* is the monthly value of Baker et al. (2015) measure for policy uncertainty index for Europe. *capital* is the banking group's risk weighted assets to total assets (capital ratio) lagged by one quarter. *bank controls* are the banks' liquidity ratio, a dummy for the five largest banking groups and a dummy for mutual banks. *macro controls* are the unemployment rate, the inflation rate and the industrial production rate for Italy, lagged by one quarter. Some covariates included in the model are not reported to imprve clarity. Sample period is 2003:08 to 2012:12. Errors are clustered at the bank group*month level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Panel a. The impact of uncertainty : alternative measures.

	approval							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
uncertainty is	VSTOXX	VSTOXX	VSTOXX	VSTOXX	EPU IT	EPU IT	EPU IT	EPU IT
uncertainty	-0.002***	-0.002*	-0.002*		-0.051***	-0.096***	-0.086***	
	(0.001)	(0.001)	(0.001)		(0.011)	(0.018)	(0.011)	
eonia	-0.478	-0.089	-1.217*		-1.232**	-1.987***	-2.928***	
	(0.564)	(1.156)	(0.725)		(0.492)	(0.718)	(0.444)	
uncertainty *eonia	0.085***	0.102**	0.103***		2.975***	4.619***	4.683***	
	(0.023)	(0.046)	(0.033)		(0.429)	(0.614)	(0.481)	
capital *uncertainty		0.000	-0.000	0.000				0.003**
		(0.000)	(0.000)	(0.000)				(0.001)
capital *eonia		-0.032	0.072	0.062		0.060	0.100***	0.165***
		(0.072)	(0.051)	(0.074)		(0.039)	(0.032)	(0.058)
capital *uncertainty *eonia		-0.002	-0.001	-0.002				-0.151***
		(0.003)	(0.002)	(0.003)				(0.056)
bank controls	yes	yes	yes	yes	yes	yes	yes	yes
firm rating	yes	yes	yes	-	yes	yes	yes	-
macro controls	yes	yes	yes	-	yes	yes	yes	-
bank FE	no	no	yes	yes	no	no	yes	yes
firm FE	no	no	yes	-	no	no	yes	-
firm*month FE	no	no	no	yes	no	no	no	yes
observations	2259892	2259892	2078492	260390	2259892	2259892	2078492	260390
estimation	OLS	OLS	panel	panel	OLS	OLS	panel	panel

Note: these regressions examine the effect of an increase in various proxies of uncertainty on the probability that an application is approved, considering the transmission via bank capital. The dependent variable is *approval*, taking value 1 if the loan application is approved. $VSTOXX$ is the monthly average of the VSTOXX index. *EPU IT* is the monthly value of Baker et al. (2015) measure for policy uncertainty index for Italy. *capital* is the banking group's risk weighted assets to total assets (capital ratio) lagged by one quarter. *bank controls* are the banks' liquidity ratio, a dummy for the five largest banking groups and a dummy for mutual banks. *macro controls* are the unemployment rate, the inflation rate and the industrial production rate for Italy, lagged by one quarter. Some covariates included in the model are not reported to imprve clarity. Sample period is 2003:08 to 2012:12. Errors are clustered at the bank group*month level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Panel b. The impact of uncertainty : alternative measures (continued).

	approval							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
uncertainty is	Dis CPI	Dis CPI	Dis CPI	Dis CPI	Dis BB	Dis BB	Dis BB	Dis BB
uncertainty	-0.001***	-0.001**	-0.001***		-0.001***	-0.001***	-0.001***	
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	
eonia	-1.850***	-1.376	-2.841***		-2.534***	-2.441**	-3.681***	
	(0.678)	(0.852)	(0.729)		(0.781)	(0.970)	(0.620)	
uncertainty *eonia	0.034***	0.038***	0.042***		0.034***	0.039***	0.042***	
	(0.009)	(0.009)	(0.009)		(0.008)	(0.009)	(0.006)	
capital *uncertainty				0.000*				0.000**
				(0.000)				(0.000)
capital *eonia		-0.040	0.063	0.217***		0.001	0.121***	0.182**
		(0.052)	(0.049)	(0.074)		(0.051)	(0.044)	(0.073)
capital *uncertainty *eonia				-0.002***				-0.001**
				(0.001)				(0.001)
bank controls	yes	yes	yes	yes	yes	yes	yes	yes
firm rating	yes	yes	yes	-	yes	yes	yes	-
macro controls	yes	yes	yes	-	yes	yes	yes	-
bank FE	no	no	yes	yes	no	no	yes	yes
firm FE	no	no	yes	-	no	no	yes	-
firm*month FE	no	no	no	yes	no	no	no	yes
observations	2259892	2259892	2078492	260390	2259892	2259892	2078492	260390
estimation	OLS	OLS	panel	panel	OLS	OLS	panel	panel

Note: these regressions examine the effect of an increase in various proxies of uncertainty on the probability that an application is approved, considering the transmission via bank capital. The dependent variable is *approval*, taking value 1 if the loan application is approved. *Dis CPI* is the cross-sectional standard deviation of the forecasts isued by the professional forecasters surveyed by Consensus Economics for headline consumer inflation in the euro zone. *Dis BB* is defined likewise for the euro zone budget balance. *capital* is the banking group's risk weighted assets to total assets (capital ratio) lagged by one quarter. *bank controls* are the banks' liquidity ratio, a dummy for the five largest banking groups and a dummy for mutual banks. *macro controls* are the unemployment rate, the inflation rate and the industrial production rate for Italy, lagged by one quarter. Some covariates included in the model are not reported to imprve clarity. Sample period is 2003:08 to 2012:12. Errors are clustered at the bank group*month level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3. The interaction between uncertainty and bank characteristics.

	approval					
	(1)	(2)	(3)	(4)	(5)	(6)
EPU EU	-0.096***		-0.057***		-0.055***	
	(0.006)		(0.003)		(0.005)	
eonia	-3.886***		-1.437***		-1.656***	
	(0.364)		(0.251)		(0.284)	
EPU EU*eonia	3.763***		2.139***		2.143***	
	(0.334)		(0.210)		(0.239)	
x*EPU	0.002***	0.000	0.018	0.012	-0.002	0.028**
	(0.000)	(0.000)	(0.012)	(0.010)	(0.005)	(0.012)
x* eonia	0.121***	0.038	-0.189	-0.261	0.392	2.263***
	(0.021)	(0.028)	(0.611)	(0.671)	(0.369)	(0.840)
x*EPU*eonia	-0.084***	-0.047**	-0.818	-0.528	-0.007	-1.366**
	(0.018)	(0.021)	(0.537)	(0.493)	(0.315)	(0.637)
x is	liquidity ratio	liquidity ratio	large bank	large bank	mutual bank	mutual bank
bank controls	yes	yes	yes	yes	yes	yes
firm controls	yes	-	yes	-	yes	-
macro controls	yes	-	yes	-	yes	-
bank FE	yes	yes	yes	yes	yes	yes
firm FE	yes	-	yes	-	yes	-
firm*month FE	no	yes	no	yes	no	yes
observations	2078492	260390	2078492	260390	2078492	260390
estimation	panel FE	panel FE	panel FE	panel FE	panel FE	panel FE

Note: these regressions examine the effect of an increase in uncertainty on the probability that an application is approved, considering the transmission via different bank characteristics. The dependent variable is *approval*, taking value 1 if the loan application is approved. *EPU EU* is the monthly value of Baker et al. (2015) measure for policy uncertainty index for Europe. *liquidity ratio* is the banking group's liquidity ratio lagged by one quarter. *large bank* and *mutual bank* are dummies singling out intermediaries respectively belonging to the top 5 banking groups and that are mutual banks. *bank controls* are the banks' liquidity ratio, a dummy for the five largest banking groups and a dummy for mutual banks. *macro controls* are the unemployment rate, the inflation rate and the industrial production rate for Italy, lagged by one quarter. Some covariates included in the model are not reported to imprve clarity. Sample period is 2003:08 to 2012:12. Errors are clustered at the bank group*month level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. The compositional effects of uncertainty on loan approval.

	approval					
	Panel (a)					
	(1)	(2)	(3)	(4)	(5)	(6)
bank control* firm control* EPU	0.001*	0.000	0.001**	-0.000*	0.000	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
bank control* firm control* EONIA	-0.035	-0.022	0.095***	0.016*	-0.007	0.043***
	(0.028)	(0.042)	(0.021)	(0.012)	(0.013)	(0.013)
firm control is	big firm	good rating	same province	big firm	good rating	same province
bank control is	capital ratio	capital ratio	capital ratio	liquidity ratio	liquidity ratio	liquidity ratio
observations	190304	222614	238095	311761	365505	390648
	Panel (b)					
	(1)	(2)	(3)	(4)	(5)	(6)
bank control* firm control* EPU	0.005	0.006	0.038***	-0.005	0.001	0.010
	(0.009)	(0.013)	(0.008)	(0.004)	(0.005)	(0.008)
bank control* firm control* EONIA	0.558	0.119	0.118	0.091	-0.514**	0.494
	(0.541)	(0.770)	(0.463)	(0.236)	(0.225)	(0.396)
firm control is	big firm	good rating	same province	big firm	good rating	same province
bank control is	mutual bank	mutual bank	mutual bank	top5 bank	top5 bank	top5 bank
observations	318793	399222	399222	318793	373471	399222
bank*month FE	yes	yes	yes	yes	yes	yes
firm*month FE	yes	yes	yes	yes	yes	yes
estimation	panel FE	panel FE	panel FE	panel FE	panel FE	panel FE

Note: these regressions examine the heterogeneity of the baseline effect across firm and bank characteristics. The dependent variable is *approval*, taking value 1 if the loan application is approved. *EPU* is an index of policy uncertainty provided by Baker (2012) for Europe. *bank controls* are defined as in table 4. *firm controls* are as defined in the table: *big firm* takes value 1 if the firm's assets are above the median of the distribution; *good rating* is a dummy that takes value 1 if the firm's rating at the moment of the application is in one of the top three bins (of nine); *same province* is a dummy that takes value 1 if the applying firm is located in the same province as the headquarters of the bank that receives the application. Some covariates included in the model are not reported to imprve clarity. Sample period is 2003:08 - 2012:12. Robust standard errors in parentheses. Errors are triple clustered at the bank, firm and month level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The impact of uncertainty on postponed applications.

	postponed					
	(1)	(2)	(3)	(4)	(5)	(6)
EPU	0.029***	0.030***	0.024**			
	(0.006)	(0.006)	(0.011)			
ΔEPU				0.037***	0.028***	0.027***
				(0.007)	(0.006)	(0.008)
bank controls	yes	yes	yes	yes	yes	yes
firm rating	yes	yes	-	yes	yes	-
macro controls	yes	yes	-	yes	yes	-
bank FE	no	no	yes	no	no	yes
firm FE	no	yes	-	no	yes	-
firm*year FE	no	no	yes	no	no	yes
observations	399024	240944	78424	393691	236469	77699
estimation	OLS	panel FE	panel FE	OLS	panel FE	panel FE

Note: these regressions examine the effect of an increase in uncertainty on the probability that the decision on an application that is eventually approved is postponed to the next one or two month. The dependent variable is *postponed*, taking value 1 if the loan application is approved in the month(s) following the first one after reception. *EPU* is the monthly value of Baker's policy uncertainty index for Europe (3-month delta and levels). Sample period is 2003:08 to 2012:12. Robust standard errors in parentheses. Errors are clustered at the bank group*month level. *** p<0.01, ** p<0.05, * p<0.1.

Annex

A. Data description

Monthly data on loan applications are corrected for mergers and acquisition by discarding the applications advanced to the acquiring bank by costumers of the acquired bank in the quarter before the completion of the M&A. To account for the change in reporting threshold (January 2009) we consider only the applications that were not affected by it. Both correction are relaxed in the robustness tests in section 6 Other features of loan applications and uncertainty indicators are discussed in Section 3 of the paper.

To these data we merge bank balance sheet information drawn from the Bank of Italy supervisory records. We use consolidated quarterly series on banks' Tier 1 capital ratio, liquidity ratio (defined as the ratio of cash and securities to total assets), a dummy to single out banks belonging to the five largest groups and one for mutual banks. Information on firms comes from the proprietary database managed by Cerved Group®, from which we initially randomly selected the firms in our data. The dataset gives us yearly information on total assets and the Cerved® rating, a synthetic indicator of the firm's overall credit quality.[18] We also separately collect information on the distance between the firms' headquarters and the offices of the banks that receive their credit applications.

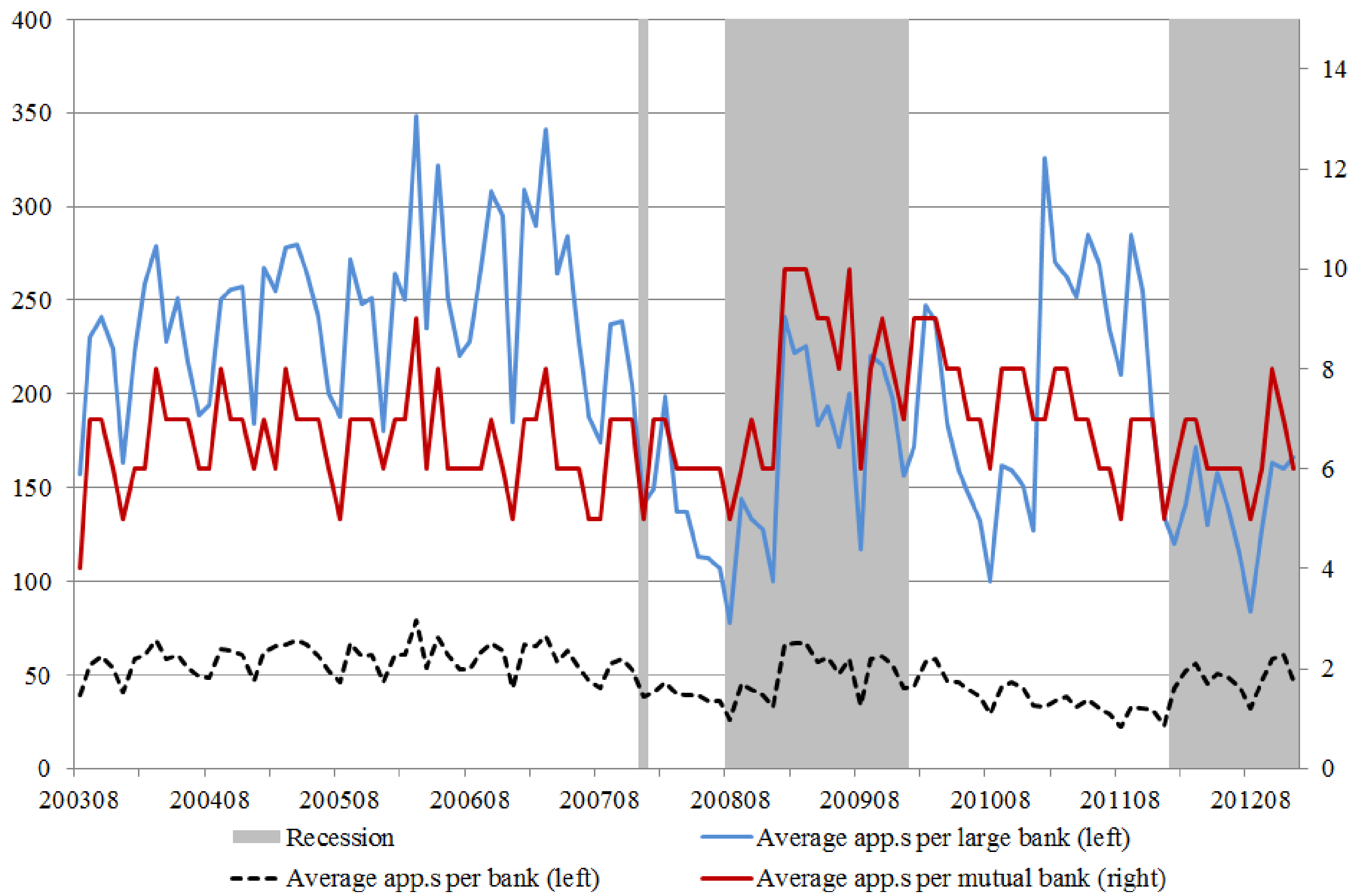
Our baseline monetary policy indicator is the monthly average of daily EONIA rates, as in Jiménez *et al.* (2014). Using EONIA has two important advantages. The first one is that EONIA might capture at least in part the impact of unconventional monetary interventions that we do not account for explicitly in the regressions (Ciccarelli *et al.*, 2015). The second one is that, given its short (overnight) maturity, EONIA is relatively less affected by liquidity and credit risk premia. This point is clearly critical for our purposes: using interest rates that are heavily driven by agents' risk perceptions would greatly complicate our attempts to disentangle uncertainty effects from the ordinary bank lending channel of monetary policy. In the robustness analysis we use a one-month Euribor rate, though this is less attractive because it might have been partly driven by risk-related concerns, particularly after 2007 (Angelini *et al.* 2011). Our main macroeconomic control variables are the monthly series on inflation, industrial production and the unemployment rate in Italy available from the European Central Bank's Statistical Data Warehouse. Inflation is the quarterly growth rate in the Harmonized Consumer Price Index (HCPI) that excludes food and energy (a proxy of "core" inflation). Since GDP is not available on a monthly basis, we measure economic activity with the quarterly growth in industrial production and unemployment. In addition to these, in the robustness analysis we use two measure of expectations on future economic activity constructed with survey data from the European Commission. The first one is the Economic Sentiment Indicator (ESI), a broad sentiment measure published directly by the European Commission which includes household and firm expectations and perceptions on the current state of the economy. The second one is an "expected activity" indicator that we construct by averaging firms' expectations on their own production levels, employment and selling prices over the following 12 months.

[18]Cerved computes a z-score (rating) based on the methodology developed in Altman (1994) to all firms that present a balance sheet sufficiently detailed to compute the indicator.

The variables in the data are organized in such a way to reproduce the information set available to the evaluating bank in the month when the application is formulated. More precisely, data on the monetary policy rate and on uncertainty are contemporaneous; the other macroeconomic variables and information on banks refer to the quarter preceding the loan application; and the firm-level variables refer to the end of the previous year.

B. Figures

Figure A1. Number of applications per bank category.



Note: The red line displays the average number of application received in a certain month by mutual banks. The blue line ditto for banks belonging to one of the top five banking groups. The black dotted link is the average applications per banks in the sample.

C. Additional tables

Table A2. Postponed applications: robustness tests.

	posponed					
	(1)	(2)	(3)	(4)	(5)	(6)
EPU	0.026***	0.026***	0.024**			
	(0.007)	(0.008)	(0.011)			
eonia	-0.258	-0.600	0.072			
	(0.403)	(0.458)	(1.590)			
ΔEPU				0.036***	0.027***	0.026***
				(0.007)	(0.006)	(0.008)
Δeonia				-2.510	-1.966	-1.396
				(3.232)	(2.692)	(2.879)
bank controls	yes	yes	yes	yes	yes	yes
firm rating	yes	yes	-	yes	yes	-
macro controls	yes	yes	-	yes	yes	-
bank FE	no	no	yes	no	no	yes
firm FE	no	yes	-	no	yes	-
firm*year FE	no	no	yes	no	no	yes
observations	399024	240944	78424	393691	236469	77699
estimation	OLS	panel FE	panel FE	OLS	panel FE	panel FE

Note: these regressions examine the effect of an increase in uncertainty on the probability that the decision on an application that is eventually approved is postponed to the next one or two month. The dependent variable is *postponed*, taking value 1 if the loan application is approved in the month(s) following the first one after reception. *EPU* is the monthly value of Baker's policy uncertainty index for Europe (3-month delta and levels). Sample period is 2003:08 to 2012:12. Robust standard errors in parentheses.Errors are clustered at the bank group*month level. *** p<0.01, ** p<0.05, * p<0.1.

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Table A1. Correlation between uncertainty and postponed applications.

	$EONIA$	EPU	$VSTOXX$	$Volatility$	$Disagree^{CPI}$	$Disagree^{BB}$
A. Contemporaneous correlation with *Postpone*						
Statistic	-0.153	0.170	0.215	0.145	0.098	0.163
p-value	*0.11*	*0.07*	*0.02*	*0.12*	*0.30*	*0.08*
B. Granger causality test: $X$is not predicted by *Postpone*						
Statistic	2.840	1.217	0.536	1.530	1.308	0.397
p-value	*0.01*	*0.30*	*0.78*	*0.18*	*0.26*	*0.88*
C. Granger causality test: Xdoes not predict *Postpone*						
Statistic	1.649	2.444	1.519	1.036	1.365	2.277
p-value	*0.14*	*0.031*	*0.18*	*0.41*	*0.24*	*0.04*

Note: the table documents the comovements between Postpone, which is defined as the share of loan applications that are approved with a delay of one month or more over all approved applications, and the macroeconomic indicators listed along the colums: the EONIA rate, the Economic Policy Uncertainty index of Baker et al. (2012), VSTOXX, the volatility of Eurostoxx 50 share prices and forecasters disagreement on CPI inflation or the government budget balance of the eurozone. For each indicator, panel A report the contemporaneous correlation with Postpone, panel B a test of the null hypothesis that the indicator is not predicted by Postpone, and panel C a test of the null hypothesis that Postpone is not predicted by the indicator. The tests are run using bivariate regressions that include six lags of Postpone and the indicator of interest. The sample is August 2003 to December 2012.

Table A3. Postponed applications: robustness to alternative measures of uncertainty.

				Panel (a) *posponed*				
uncertainty is	ΔVSTOXX	ΔVSTOXX	ΔEPU IT	ΔEPU IT	ΔDisagr BB	ΔDisagr BB	ΔDisagr CPI	ΔDisagr CPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
uncertainty	0.003***	0.003***	0.006	0.014	0.000	0.000	-0.001***	-0.001***
	(0.001)	(0.001)	(0.008)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)
observations	399024	78424	399024	78424	399024	78424	399024	78424
				Panel (b) *posponed*				
uncertainty is	VSTOXX	VSTOXX	EPU IT	EPU IT	Disagr BB	Disagr BB	Disagr CPI	Disagr CPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
uncertainty	0.002***	0.003***	0.038***	0.032**	0.000***	0.000	-0.000	-0.001***
	(0.000)	(0.001)	(0.007)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)
observations	399024	78424	399024	78424	399024	78424	399024	78424
bank controls	yes	yes	yes	yes	yes	yes	yes	yes
firm rating	yes	-	yes	-	yes	-	yes	-
macro controls	yes	-	yes	-	yes	-	yes	-
bank FE	no	yes	no	yes	no	yes	no	yes
firm FE	no	-	no	-	no	-	no	-
firm*year FE	no	yes	no	yes	no	yes	no	yes
estimation	OLS	panel FE	OLS	panel FE	OLS	panel FE	OLS	panel FE

Note: these regressions examine the effect of an increase in uncertainty on the probability that the decision on an application that is eventually approved is postponed to the next one or two months. The dependent variable is *postponed*, taking value 1 if the loan application is approved in the month(s) following the first one after reception. *EPU It* is the monthly value of Baker's policy uncertainty index for Italy. *VSTOXX* is the monthly average of the VSTOXX index. *Disagreement BB* and *Disagreement CPI* are the cross-sectional standard deviation of the forecasts issued by the professional forecasters surveyed by Consensus Economics fore the euro zone budget balance and for the headline consumer inflation in the euro zone. *Macro controls* include y-o-y delta unemployment, consumer inflation and industrial production for Italy, lagger by one quarter (all: 3-month delta and levels). Sample period is 2003:08 to 2012:12. Robust standard errors in parentheses.Errors are clustered at the bank group*month level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4. Postponed applications: heterogeneity across banks.

	postponed			
	(1)	(2)	(3)	(4)
EPU	0.027**	0.045***	0.024***	0.066***
	(0.012)	(0.012)	(0.007)	(0.020)
x	-0.001	0.001	-0.039***	-0.105***
	(0.001)	(0.001)	(0.011)	(0.022)
EPU*x	0.000	-0.001	0.029***	0.039***
	(0.001)	(0.001)	(0.008)	(0.019)
x is	capital ratio	liquidity ratio	same province	small firms
bank controls	yes	yes	yes	yes
firm rating	yes	yes	yes	yes
macro controls	yes	yes	yes	yes
bank FE	yes	yes	yes	yes
firm FE	yes	yes	yes	yes
observations	240944	240944	235456	191849
estimation	panel FE	panel FE	panel FE	panel FE

Note: these regressions examine heterogeneity across bank characteristics of the effect of an increase in uncertainty on the probability that the decision on an application that is eventually approved is postponed to the next one or two months. The dependent variable is *postponed*, taking value 1 if the loan application is approved in the month(s) following the first one after reception. *EPU* is the monthly value of Baker's policy uncertainty index for Europe (3-month delta and levels). *bank controls* as defined in the table and described in table 4. Sample period is 2003:08 to 2012:12. Robust standard errors in parentheses. Errors are clustered at the bank group*month level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5. The impact of uncertainty on loan approvals: robustness to fixed effects.

	approval		
	(1)	(2)	(3)
EPU EU	-0.039***	-0.035***	-0.056***
	(0.006)	(0.004)	(0.004)
eonia	-1.133**	-0.759***	-1.617***
	(0.486)	(0.281)	(0.272)
EPU EU*eonia	1.753***	1.623***	2.151***
	(0.329)	(0.235)	(0.220)
bank controls	yes	yes	yes
firm rating	yes	yes	yes
macro controls	yes	yes	yes
bank FE	no	yes	yes
firm FE	no	no	yes
observations	2259892	2259883	2078492
estimation	OLS	panel FE	panel FE

Note: these regressions examine the effect of an increase in uncertainty on the probability that an application is approved. The dependent variable is *approval*, taking value 1 if the loan application is approved. *EPU* is the monthly value of Baker's policy uncertainty index for Europe. Sample period is 2003:08 to 2012:12. Robust standard errors in parentheses. Errors are clustered at the bank group* month level. *** p<0.01, ** p<0.05, * p<0.1.

Table A6. The impact of uncertainty on loan approvals: robustness to uncertainty measures.

	approval			
uncertainty is	VSTOXX	EPU IT	Disagr BB	Disagr CPI
	(1)	(2)	(3)	(4)
uncertainty	-0.002***	-0.074***	-0.001***	-0.001***
	(0.000)	(0.006)	(0.000)	(0.000)
eonia	-0.488	-1.937***	-2.211***	-2.459***
	(0.374)	(0.272)	(0.374)	(0.341)
uncertainty*eonia	0.092***	3.879***	0.039***	0.035***
	(0.015)	(0.294)	(0.004)	(0.003)
bank controls	yes	yes	yes	yes
firm rating	yes	yes	yes	yes
macro control	yes	yes	yes	yes
bank FE	no	no	no	no
firm FE	yes	yes	yes	yes
observations	2078492	2078492	2078492	2078492
estimation	panel FE	panel FE	panel FE	panel FE

Note: these regressions examine the effect of an increase in uncertainty on the probability that an application is approved. The dependent variable is *approval*, taking value 1 if the loan application is approved. $EPU\ It$ is the monthly value of Baker's policy uncertainty index for Italy. $VSTOXX$ is the monthly average of the VSTOXX index. $Disagreement\ BB$ and $Disagreement\ CPI$ are the cross-sectional standard deviation of the forecasts issued by the professional forecasters surveyed by Consensus Economics for the euro zone budget balance and for the headline consumer inflation in the euro zone. Macro controls include y-o-y delta unemployment, consumer inflation and industrial production for Italy, lagger by one quarter. Sample period is 2003:08 to 2012:12. Robust standard errors in parentheses. Errors are clustered at the bank group* month level. *** p<0.01, ** p<0.05, * p<0.1.

Table A7. The impact of uncertainty on loan approvals: robustness to endogeneity and mismeasurement.

	approval							
	with lags	lagged relationship	euribor	with expectations	large firms only	no threshold correction	no M&A correction	with month dummies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EPU	-0.053***		-0.064***	-0.069***	-0.013***	-0.046***	-0.062***	-0.064***
	(0.005)		(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
eonia	-7.039***			-1.632***	-0.338	-2.082***	-2.253***	-2.182***
	(0.935)			(0.230)	(0.293)	(0.227)	(0.328)	(0.216)
EPU*eonia	1.741***			2.225***	0.574***	2.054***	2.537***	2.427***
	(0.205)			(0.179)	(0.208)	(0.192)	(0.224)	(0.174)
EPU_l1	-0.001	-0.061***						
	(0.004)	(0.004)						
eonia_l1	1.132	-2.029***						
	(1.139)	(0.296)						
(EPU*eonia)_l1		2.612***						
		(0.230)						
Euribor			-0.019***					
			(0.002)					
Euribor*EPU			0.022***					
			(0.002)					
bank controls	yes	yes	yes	yes	yes	yes	yes	yes
firm rating	yes	yes	yes	yes	yes	yes	yes	yes
macro control	yes	yes	yes	yes	yes	yes	yes	yes
bank FE	yes	yes	yes	yes	yes	yes	yes	yes
firm FE	yes	yes	yes	yes	yes	yes	yes	yes
macro control	yes	yes	yes	yes	yes	yes	yes	yes
observations	2752751	2752751	2752751	2752751	238955	2752751	3098885	2752751
estimation	panel FE	panel FE	panel FE	panel FE	panel FE	panel FE	panel FE	panel FE

Note: these regressions examine the heterogeneity of the baseline effect across different specifications. The dependent variable is *approval*, taking value 1 if the loan application is approved. *EPU* is an index of policy uncertainty provided by Baker (2012) for Europe. *Macro controls for expectations* include two lags of the monthly y-o-y growth of the Economic Sentiment indicator for Italy, as well as two lags of the monthly average of firms' expectations of production, employment and selling prices over the following 12 months. Macro controls include y-o-y delta unemployment, consumer inflation and industrial production for Italy, lagger by one quarter. Some covariates are not reported to improve clarity. Sample period is 2003:08 - 2012:12. Robust standard errors in parentheses. Errors are clustered at the bank group*month level. *** p<0.01, ** p<0.05, * p<0.1.

Table A8. The impact of uncertainty on loan approvals: robustness tests.

	approval			*approval*	
	(1)	(2)		(3)	(4)
EPU_l1	-0.058***		EPU	-0.064***	
	(0.010)			(0.009)	
eonia_l1	-1.362**		euribor	-0.013**	
	(0.573)			(0.006)	
(EPU*eonia)_l1	2.943***		EPU*euribor	0.024***	
	(0.462)			(0.004)	
capital*EPU_l1	0.002**	0.001	capital*EPU	0.002***	0.002*
	(0.001)	(0.001)		(0.001)	(0.001)
capital*eonia_l1	-0.003	0.056	capital*euribor	0.000	0.001**
	(0.037)	(0.054)		(0.000)	(0.001)
capital*EPU_l1 *eonia_l1	-0.066***	-0.026	capital*EPU *euribor	-0.001**	-0.001*
	(0.025)	(0.036)		(0.000)	(0.000)
bank controls	yes	yes		yes	yes
firm rating	yes	-		yes	-
macro controls	yes	-		yes	-
bank FE	yes	yes		yes	yes
firm FE	yes	-		yes	-
firm*month FE	no	yes		no	yes
observations	2259892	260390		2259892	260390
estimation	panel FE	panel FE		panel FE	panel FE

Note: these regressions examine the robustness of the baseline findings. The dependent variable is *approval*, taking value 1 if the loan application is approved. EPU l1 is the lagged monthly value of Baker et al. (2015) measure for policy uncertainty index for Europe. eonia l1 is lagged monthly eonia value. *capital* is the banking group's risk weighted assets to total assets (capital ratio) lagged by one quarter. *bank controls* are the banks' liquidity ratio, a dummy for the five largest banking groups and a dummy for mutual banks. *macro controls* are the unemployment rate, the inflation rate and the industrial production rate for Italy, lagged by one quarter. Some covariates are not reported to improve clarity. Sample period is 2003:08 to 2012:12. Robust standard errors in parentheses. Errors are clustered at the bank group* month level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.