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Abstract

This paper presents a two-step procedure to derive a credit crunch indicator for the Italian manufacturing sector. Using qualitative firm-level data over the years 2008-2018, nonlinear discrete panel data techniques are first applied in order to identify the loan supply curve controlling for firm-specific observable characteristics. In the subsequent step, the variation of the estimated supply curve that cannot be explained by proxies for loan demand is interpreted as the degree of credit squeeze prevailing in the economy at a given point in time. The empirical evidence shows that credit crunch episodes are less likely to occur during periods of sustained economic growth, or when credit availability for the manufacturing sector is relatively abundant. In contrast, a tight monetary policy stance or a worsening of the quality of banking balance sheets tend to increase the likelihood of experiencing a credit squeeze.

JEL: G30; G32; C23

Keywords: business survey, credit crunch, access to credit

1. Introduction

During periods of financial distress, troubles affecting the credit system are likely to spread to the real sector, especially in countries where the banking sector is the most relevant financing channel to the business sector and/or the productive structure is predominantly based on small and medium enterprises (Ferrando et al., 2014; Berger and Udell, 2006). In this respect, the Italian case looks particularly interesting not only because of the historical reliance of its productive structure on banks' external funds (Manaresi and Pierri, 2018) but also in view of the widely documented existence of credit rationing for most of the Italian firms (Guiso, 1998; Finaldi Russo and Rossi, 2001; Becchetti and Trovato, 2002; Trovato and Alfo, 2006; Minetti and Zhu, 2011). It therefore comes as no surprise that the financial turmoil in the aftermath of the Global Recession and the sovereign debt crisis has stimulated a lively debate on the existence of credit crunch for the case of the Italian economy over the most recent years (see, among others, Presbitero et al., 2016).

From a theoretical perspective, credit crunch episodes are commonly defined as significant shifts in the supply curve for loans when a tightening of credit conditions occurs (Bernanke and Lown, 1991; Udell, 2009). In such circumstances seemingly eligible borrowers find hard to be financed due to asymmetric information and agency problems, forcing firms that rely on bank lending as a source of external finance to alternative funding channels (for instance, corporate debt issuances) or, when this is not a viable option, to insolvency. During bad times, however, it might also be the case that firms tend to demand less credit because investment plans are likely to be postponed, so that identifying whether the contraction in bank lending originates from a shift in supply or demand is a key empirical issue (Bernanke and Gertler, 1995; Oliner and Rudebusch, 1996). Accordingly, a proper identification of credit crunch episodes calls for identifying variations in the loan supply curve that cannot be explained by determinants of loan demand, including the creditworthiness of borrowers or the banks’ opportunity costs of providing risky loans.

Against this backdrop, this work presents a micro-macro econometric approach to construct a credit crunch indicator for the Italian economy by exploiting the information content of firm-level (qualitative) data inquiring on their appraisal of the prevailing lending policy of the banking sector. The proposed approach has proved itself well suited to the purpose, as firstly documented by the work of Borensztein and Lee (2002) on the effects of the financial crisis and the ensuing credit crunch in Korea. Using German data, instead, Rottman and Wollmershauser (2013) have estimated the probability of a restrictive loan supply policy, while Fidrmuc and Hainz (2013) have studied how differences in regulation influence competition between domestic and foreign banks. For the case of Italy, Pigini et al. (2016) have used a sample of manufacturing firms to document state dependency in access to credit, that is the occurrence that firms having faced a credit contraction in the past may suffer from a negative impact on the outcome of a subsequent loan application. Using the same dataset of Pigini et al. (2016), Presbitero et al. (2016) have tried to address the question whether troubles in the banking system reflected in the bankruptcy of Lehman Brothers in September 2008 have spurred a credit crunch.

Here we build on an updated version of the estimation sample of Pigini et al. (2016) and Presbitero et al. (2016) to derive a credit crunch indicator by following a two-step procedure along the lines of Rottman and Wollmershauser (2013). Specifically, we apply nonlinear discrete outcome panel-data model to regress the responses to firms' assessment about the access to credit on a large set of observable firm-specific characteristics (like firm size, current and expected liquidity conditions, ability to operate abroad, current domestic and foreign order books, demand expectations) and regional controls (namely, export propensity, quality of credit markets, efficiency of the judicial system). The regression model also allows for a set of quarterly time dummies whose coefficients (and in particular the associated average probability effects) are interpreted as (unobserved) factors determining banks' loan supply unrelated to the creditworthiness of borrowers. Subsequently, the estimated time dummies are regressed on a synthetic indicator, which distils information about firms' demand for banking loans, including the opportunity costs of providing risky loans or the corporate spread (i.e. the difference between the corporate borrowing rate and the Euribor rate). As in Rottman and Wollmershauser (2013), the residuals of the second-stage are interpreted as shifts of the loan supply curve: the more positive the contribution of the residual term to the firms' perception of a restrictive willingness to lend (holding constant the determinants of loan demand), the higher the likelihood that the economy has experienced a credit crunch episode.

Using monthly data covering the period from March 2008 to June 2018, we document that the proposed credit crunch indicator flags the Global Recession of 2008-2009 as a period of credit crunch for the Italian economy followed by a relatively accommodating *intermezzo* coming to a halt with the eruption of the second recessionary episode in 2012-2014. In the most recent period, the unconventional monetary interventions by ECB seem to have somewhat improved banks' willingness to lend as witnessed by the sizeable retracement of the indicator from its historical maxima, although signs of less favorable credit conditions emerge towards the end of the estimation sample. In order to identify the most relevant factors that might affect the evolvement over time of the proposed indicator, we have also conducted some scenario analyses under realistic data-availability conditions in order to cope with the publication calendar of the series involved in the regression (Leduc and Sill, 2013; Girardi, 2014). The empirical evidence based on fractional logit and probit regression models shows a negative and statistically significant effect of GDP growth and (relative) credit availability for the manufacturing sector on the probability of an episode of credit crunch. In contrast, rising interest rates or a worsening of the quality of banking balance sheets increase the likelihood of experimenting a credit squeeze. All in all, the model is able to capture a large share of total variability of the target series, with the GDP dynamics being by far the most relevant determinant of credit squeeze. These conclusions are robust with respect to a number of alternative specifications and estimation techniques.

The rest of paper is organized as follows. Section 2 presents the data and the empirical framework of reference. The proposed credit crunch indicator and the scenario analyses are discussed in Sections 3 and 4. Robustness checks and extensions with respect to the baseline specification are presented in Section 5. Concluding remarks follow.

2. Firm heterogeneity and access to credit: a micro-econometric perspective

2.1 Firm-specific conditions to access to credit

Our analysis relies on the monthly firm-level data drawn from the manufacturing tendency survey carried out by the Italian National Institute of Statistics (ISTAT) within the Joint Harmonized EU Programme of Business and Consumer Surveys (European Commission, 2017). The survey covers non-financial firms with at least five employees, operating in the manufacturing sector. Data are typically qualitative, meaning that the survey conveys firms' opinions and the respondent firms have usually to choose among three possible answers arranged on a Likert scale. The sample has a longitudinal structure and it is stratified upon three dimensions: firm size, sectors of economic activity (NACE Rev. 2) and geographical areas (NUTS I level). The sample size is of about 4,000 statistical units each month and embraces the period from March 2008 to June 2018. In particular, our estimation sample covers both the global financial crisis and the subsequent turmoil related to the sovereign debt crisis, when credit constraints were particularly important and had huge impact on economic outcomes (see, for instance Chodorow-Reich, 2014).

A specific credit section - added to the survey since March 2008 - provides detailed information on firms' assessment of recent short-term developments regarding their access to finance and covers bank-firm relationships. It is worth noticing that firms' assessment about banks' loan supply conditions cannot be considered *a-priori* as a valid proxy of credit constraints because firms' answers to the questionnaire refer to a change in the credit conditions and are not informative about the intensity (that is the level) of the credit restrictions. Nonetheless, they may be conceived as a proxy for credit access, capturing in this way both formal and informal constraints (Ferrando et al. 2015). From a theoretical perspective, it is possible to interpret firms' appraisal of banks' loan supply conditions as informative about the location of the loan supply curve (Rottmann and Wollmershauser, 2013). In turn, working solely on the loan supply curve makes it possible to establish a direct link to the concept of credit crunch, which is typically defined as a significant contraction in the credit supply reflected in a tightening of credit conditions (Udell, 2009)[1].

Qualitative information is collected at the level of the j-th firm (with $j = 1, \dots, J$) doing business in the s-th sector (with $s = 1, \dots, S$), located in region $l = 1, \dots, L$ and observed at time $t = 1, \dots, T$. In particular, firms' assessment on credit conditions ($cre_{j,l,s,t}$) - that constitutes the response variable along our empirical investigation - takes values 1, 2 and 3 according to whether firm's evaluations of credit conditions are considered as 'getting better', 'stable' or 'worsening' with respect to the previous three months, respectively.

2.2 Observable firms heterogeneity: candidate explanatory variables

In addition to firms' self-reported evaluation of the credit conditions, the survey also collects some qualitative information about the developments of businesses' economic activity, some of which

[1] On this issue, see also Costa et al. (2012).

may be used as explanatory variables in the analysis. In particular, the set of regressors includes variables aimed at capturing: (I) borrowing and liquidity conditions, (II) the degree of export orientation, (III) idiosyncratic demand shocks[2]. The survey also reports some structural information on the respondents (number of employees, economic branch and location of the economic activity); in this way, it is possible to estimate a credit crunch indicator through the lens of the firm's heterogeneity by size, sector, and location.

As for (I), there is wide consensus about the close relationship between firm size and access to external credit (Bernanke and Gertler, 1995; Carlino and DeFina, 1998; Ehrmann, 2005). In fact, firms of different size are differently exposed to credit squeeze: given a lower value of assets and a higher amount of required collateral, small firms are likely to be more credit constrained than large ones. In the balance-sheet view, given asymmetric information problems, access to credit depends on the value of firms' assets, acting as collateral. Size matters also for the bank-lending view. A tighter monetary policy reduces the amount of credit for borrowers implying that small firms, that are likely to be more dependent on intermediated credit, are more adversely affected than large firms, which can rely on easier access to other forms of external finance. Accordingly, the (logarithm of the) number of employees ($emp_{j,l,s,t}$) as a proxy for access to capital market (ability to borrow) is used. Internal liquidity may act as a key channel to finance firms' investment decisions. In this case, different liquidity degrees of equities may affect differently entrepreneurs' investments (Kiyotaki and Moore, 2012). Liquidity conditions are captured by two dummy variables indicating whether the respondent evaluates its level of liquidity with respect to operational needs ($liq_{j,l,s,t}$) as good, neither good or bad, or bad (reference category). Moreover, as firms' production decisions might also be forward looking (Galí and Gertler, 1999; Galí et al., 2001, among others), expectations are also taken into account: firms' expectations about liquidity conditions are captured by dummy variables indicating whether the firm expects over the next three months liquidity conditions will improve, remain unchanged or deteriorate (reference category) ($liq\_fwd_{j,l,s,t}$).

Concerning (II), several studies show that firm heterogeneity in export propensity occurs in each industry (for instance, Bernard and Jensen, 2004; Melitz and Ottaviano, 2008). For this reason, the incidence of firm's exports on total turnover (only available on a quarterly basis) is included in the model to measure the capacity to operate abroad ($exp_{j,l,s,t}$). In a small open economy like Italy, where the domestic cycle has a closer link with the world one, being an intense exporter gives more opportunities to raise production activity during expansions and provides greater chances for a smooth production reduction over recession phases (thanks to market diversification).

Finally, with reference to (III), it is well known that heterogeneity of firms along the cycle may also be caused by demand variations across producers (Foster et al., 2008). In the present context, we exploit information concerning domestic ($ord\_dom_{j,l,s,t}$) and foreign ($ord\_for_{j,l,s,t}$) orders to control for the cyclical demand conditions at home and abroad, respectively. More specifically, firms are asked to indicate whether the domestic and foreign demand level is high, normal or low

[2] Appendix A offers a detailed overview of the questions from the manufacturing survey used in this paper. For further details on the survey, see European Commission (2017).

over the reference period. Operationally, two dummies for both $ord\_dom_{j,l,s,t}$ and $ord\_for_{j,l,s,t}$ have been introduced, with the respective low levels being used as reference categories. As for the expected sign, they are likely to affect negatively the outcome variable. Information on demand expectations ($dem\_exp_{j,l,s,t}$) is also exploited: in detail, dummy variables indicating whether the firm expects that in the near future its demand level will increase, remain unchanged or decrease (reference category), respectively are used.

2.3 Further controls: regional characteristics

Firm-specific variables have been complemented with NUTS-3 data aimed at capturing the quality of local credit markets as well as other relevant factors characterizing the socio-economic context in which firms operate. It is widely understood that local characteristics such as financial development and institutions are likely to influence the long-term averages of the firm-level variables (Basile et al., 2014). If these local characteristics are not controlled for, the effect of firm level variables will be likely to reflect unobserved local factors that systematically affect the observed individual heterogeneity in the access to credit. As for local credit market conditions, for instance, a commonly held view is that firms, notably small and medium ones as those characterizing the Italian manufacturing sector, can only borrow locally (Petersen and Rajan, 2002). Firms' ability to access to external finance is thus directly tied to the degree of local credit market development (Guiso et al., 2013). Accordingly, the set of regressors has been extended so as to include covariates aimed at capturing the degree of local financial backwardness (bwd) and the quality of local lending policies proxied by the ratio between bad loans and overall bank loans (qlp).

At the same time, firms' productive levels are likely to reflect local market conditions, especially for the case of those selling (part of their production) abroad, as firms' export propensity (opn) is typically found to be highly affected by local spillovers, i.e. by the export decisions of nearby firms (Koenig et al., 2010). In particular, following Basile et al. (2014) a local measure of trade openness based on the export shares in sectors characterized by high dynamic world demand (namely, chemical products and pharmaceutics, computer and electronics, electrical tools, and transport) is constructed in our context. Moreover, the contractual environment in which firms operate, the local judicial system (ius) may affect firms' choices regarding investments, employment, organizational models, contractual relationships with counterparts and, thus, firms' size (Giacomelli and Menon, 2012; Boschi et al., 2014).

2.4 Dealing with non-observable heterogeneity: an Ordered Probit Model (OPM) approach

Given the qualitative nature of the response variable, we resort to the OPM framework with individual Random Effects (RE-OPM). The basic notion underlying this approach is the existence of a latent or unobserved continuous variable, in our case $cre^{*}_{j,l,s,t}$ representing firms' opinion on credit conditions, ranging from $-\infty$ to $+\infty$, which is related to a set of explanatory variables by the standard linear relationship:

$$cre^{*}_{j,l,s,t} = \beta' x_{j,l,s,t} + \gamma' w_l + z_s + \tau_t + u_{j,l,s,t} \quad (1)$$

for $j = 1, \dots, J$, $l = 1, \dots, L$, $s = 1, \dots, S$, $t = 1, \dots, T$, and where $x_{j,l,s,t}$ is a vector of time-varying regressors of firm *j*, operating in sector s, located in region *l* at time t. w_l is a vector of time-invariant regional covariates, β's and γ's denote the associated conformable parameter vectors, z_s stands for a vector of sector fixed effect, τ_t is a (quarterly) time fixed effect, while $u_{j,l,s,t}$ is a random error term (McKelvey and Zavoina, 1975). In order to fully capture the effect of individual heterogeneity, the RE-OPM approach assumes that both time-invariant, $\upsilon_{j,l,s}$, and time-varying, $\varepsilon_{j,l,s,t}$, unobserved factors may contribute to explain firms' assessments on access to credit. If we express the random error term as $u_{j,l,s,t} = \upsilon_{j,l,s} + \varepsilon_{j,l,s,t}$, model (1) can be written as:

$$cre^*_{j,l,s,t} = \beta' x_{j,l,s,t} + \gamma' w_l + z_s + \tau_t + \upsilon_{j,l,s} + \varepsilon_{j,l,s,t} \tag{2}$$

where both error components are assumed to be normally distributed and orthogonal to the set of predictors. Since the underlying variance of the composite error, $\sigma_u^2 = \sigma_\upsilon^2 + \sigma_\varepsilon^2$, is not identified, we normalise $\sigma_\varepsilon^2 = 1$, so that $\rho_{u_{j,l,s,t_1}, u_{j,l,s,t_2}} = \sigma_\upsilon^2(\sigma_\upsilon^2 + \sigma_\varepsilon^2)^{-1} = \sigma_\upsilon^2/(\sigma_\upsilon^2 + 1)$, and, thus, $\sigma_\upsilon = [\rho/(1-\rho)]^{1/2}$. Assuming a standard normal distribution for the error term yields the OPM[3].

Although $cre^*_{j,l,s,t}$ is unobserved, it is related to the integer index $cre_{j,l,s,t}$ through the relationship $cre_{j,l,s,t} = m \leftrightarrow \lambda_{m-1} < cre^*_{j,l,s,t} < \lambda_m$, with $m = 1, \dots, M$, and λ_1 through λ_{m-1}, are the unobserved thresholds defining the boundaries between different levels of $cre_{j,l,s,t}$. Given the relationship between $cre_{j,l,s,t}$ and $cre^*_{j,l,s,t}$ and indicating by Γ the set of all parameters and by $Z_{j,l,s,t}$ the model matrix, we can express the conditional cell probabilities (that is, the probability of observing a firm having a m value of $cre_{j,l,s,t}$) as:

$$\begin{aligned}
\Pr\left(cre_{j,l,s,t} = m \middle| Z_{j,l,s,t}\right) &= \Pr\left(\lambda_{m-1} \le cre^*_{j,l,s,t} \le \lambda_m\right) \\
&= \mathrm{F}\left(\frac{\lambda_{m-1} - \Gamma' Z_{j,l,s,t}}{\sqrt{1-\sigma_\upsilon^2}} \le \frac{\upsilon_{j,l,s} + \varepsilon_{j,l,s,t}}{\sqrt{1-\sigma_\upsilon^2}} \le \frac{\lambda_m - \Gamma' Z_{j,l,s,t}}{\sqrt{1-\sigma_\upsilon^2}}\right) \\
&= \mathrm{F}\left(\frac{\lambda_m - \Gamma' Z_{j,l,s,t}}{\sqrt{1-\sigma_\upsilon^2}}\right) - \mathrm{F}\left(\frac{\lambda_{m-1} - \Gamma' Z_{j,l,s,t}}{\sqrt{1-\sigma_\upsilon^2}}\right)
\end{aligned} \tag{3}$$

where $F(.)$ is the cdf for $\frac{\upsilon_{j,l,s} + \varepsilon_{j,l,s,t}}{\sqrt{1-\sigma_\upsilon^2}}$. Note that for $cre_{j,l,s,t} = 1$, the second term on the right hand side of (3) drops out and for $cre_{j,l,s,t} = M$ the first term equals 1. Estimations are performed using maximum likelihood. Individual heterogeneity is unobserved; therefore, to obtain the unconditional log-likelihood we need to integrate the conditional log-likelihood. The integration is done with the Gauss–Hermite quadrature (25 points were chosen; Greene, 2005).

Condition (3) implies that the RE-OPM is equivalent to $M-1$ binary regressions with the critical assumption (known as the parallel regression assumption, PRA) that Γ is identical across each regression. Should the PRA not hold, however, estimates may be biased and standard errors may

[3] Alternative distributions are the logit, log-logistic and the complementary log-log.

be inconsistent. Furthermore, it may be the case that the covariates have asymmetric effects within different categories, implying that the analysis based on the PRA may reveal no net effect.

Extending to longitudinal data the modelling strategy of Maddala (1983) and Terza (1985), where the hypothesis of fixed threshold parameters is relaxed by making them dependent on the predictors, Boes and Winkelmann (2010) introduce time-invariant individual effects to vary across ordinal categories. Under the hypothesis of equal slope parameters for both time-varying and time invariant regressors, that is when the systems of equalities $\beta_1 =\ldots= \beta_{M-1}$ and $\gamma_1 =\ldots= \gamma_{M-1}$ hold, the standard RE-OPM is nested into the generalized RE-OPM. The (implicit) restrictions embedded in the former can be tested against the latter by performing a χ^2-distributed LR test. Summing up, the RE-OPM gives consistent estimates under PRA. The generalized RE-OPM does not impose such a restriction, thus a test of RE-OPM consistency can be carried out by comparing the two models.

3. Estimation results: the baseline case

3.1 Controlling for unobserved heterogeneity

When estimating model (2), one should bear in mind some intricacies related to the assumption of orthogonality between error components and the set of predictors. If the explanatory variables and the individual specific effects are correlated, the RE-OPM may lead to inconsistent estimates. A possible route to overcome this issue consists in including time averages of the time-varying variables ($\bar{x}_{j,l,t}$) as additional time-invariant regressors, commonly referred to as level effects, estimating in this way the so-called Mundlak-Chamberlain's RE-OPM (Wooldridge, 2002). Modelling the expected value of the firm-specific error as a linear combination of the elements of $\bar{x}_{j,l,t}$:

$$E\left(\upsilon_{j,l,s} \middle| x_{j,l,s,t}\right) = \psi'\bar{x}_{j,l,t} \tag{4}$$

so that $\upsilon_{j,l,s} = \psi'\bar{x}_{j,l,t} + \xi_{j,l,t}$, where ψ is a conformable parameter vector and $\xi_{j,l,t}$ is an orthogonal error with respect to $\psi'\bar{x}_{j,l,t}$. Accordingly, we may recast model (2) as:

$$cre^*_{j,l,s,t} = \beta'\left(x_{j,l,s,t} - \bar{x}_{j,l,t}\right)\dot{x}_{j,l,s,t} + (\delta + \beta)'\bar{x}_{j,l,t} + \gamma' w_l + z_s + \tau_t + \xi_{j,l,t} + \varepsilon_{j,l,s,t} \qquad \text{or}$$

$$cre^*_{j,l,s,t} = \beta'\dot{x}_{j,l,s,t} + \psi'\bar{x}_{j,l,t} + \gamma' w_l + z_s + \tau_t + \xi_{j,l,t} + \varepsilon_{j,l,s,t} \tag{5}$$

with $\delta + \beta = \psi$ and $\dot{x}_{j,l,s,t} = x_{j,l,s,t} - \bar{x}_{j,l,t}$ representing the so called shock effect. Also, we assume both errors $\xi_{j,l,t}$ and $\varepsilon_{j,l,s,t}$ to be normally distributed conditionally on Z. Under these conditions, the same estimation procedure as discussed for the standard RE-OPM can be employed. Notice that the specification (2) is nested into (5) under the hypothesis that all the parameters collected in vector ψ are statistically equal to zero. This assumption can be tested through a conventional χ^2-distributed likelihood ratio (LR) test.

3.2 Empirical evidence

Column A of Table 1 presents the estimation results from a pooled-OPM specification. Overall, we find that borrowing and liquidity constraints (liq and liq_fwd, respectively) exert a statistically significant role on the response variable. The same conclusion holds true when considering idiosyncratic demand factors (ord_dom and ord_for). In contrast, firms' appraisal of access to credit turns out to be weakly affected by export propensity (exp), as well as the regional control concerning the quality of local lending policies (qlp).

Controlling for unobserved time-invariant heterogeneity [Column (B)] gives qualitatively similar results, with a sizeable increase of the likelihood function. Nonetheless, RE-OPM estimates confirm that a number of important covariates have only marginally statistical effect on the response variable. A possible piece of explanation of these findings may be a specification error in the empirical framework owing to the PRA, according to which the effects of the predictors on the response variable are identical across categories. We assess empirically such a conjecture by relaxing the PRA for those covariates that turned out to be weakly significant or statistically insignificant in the RE-OPM specification (namely, export propensity along with local time-invariant controls). Testing for PRA produces a LR test statistics (40.48) above the critical values of a distribution with 6 degrees of freedom at any significance level.

Consequently, Column (C) presents the estimation results of the generalized RE-OPM model, where Equation 1 (Equation 2) refers to the probability that the response variable moves from improving to stable (from stable to worsening) firms' assessment of access to credit. While the impact of borrowing and liquidity conditions as well as idiosyncratic demand factors remain unchanged with respect to the previous specifications, the split reveals some interesting asymmetric effects for the remaining classes of predictors. Export propensity and local controls have a significant impact on firms' assessment on access to credit in Equation 1 only. In Equation 2, instead, these predictors play no role except for the degree of openness (opn), which turns out to be marginally significant.

Table 1

As the parameters of a latent model do not have a direct interpretation *per se*, we refer to average probability effects (ape) to summarize what outcome value would be expected given the patterns observed between covariates and the outcome itself. By averaging the slope of the regression surface with respect to a given covariate across every individual firms in the data, ape's can be conceived as the average (or typical) outcome we would expect to observe were the model an accurate representation of the data-generating process for the response variable. For inference purposes, we compute standard errors of the ape's using the Delta method.

Specifically, we use the estimation results from Column (C) of Table 1 to compute the ape's for both the deviations from the individual average (shock effects) and the differences between individuals (level effects). In the discussion of the results collected in Table 2, we focus on the ape's relative to $\Pr(cre = 3)$, as we are primarily interested on the determinants of firms' appraisal of worsening conditions to external financing. It follows that the ape's for Equation 3 corresponds to the (negative) sum of the ape's relative to Equation 1 and 2. Furthermore, we concentrate the discussion of the results on the shock effects, as they mimic the typical within effects in panel models[4].

Table 2

As for firm size (emp) the results document a negative and statistically significant effect, suggesting that more productive (larger) firms tend to have a relatively less negative assessment of credit conditions than the one reported by smaller productive units. The magnitude of the ape's indicates that for an increase of 1 per cent in firm size, the average predicted probability of firms facing worsening credit access falls by around 1 per cent (see the column labelled "Shock effect" under "Equation 3"). As expected, both current and expected liquidity conditions (i.e. the rows of the Table referring to liq and liq_fwd) have a remarkable negative effect on the response variable, with the estimated magnitude of the ape's falling in the range of 7-13 percentage points. By contrast, export intensity (exp) does not exert a statistically significant impact, while an increase of (both domestic and foreign) orders or expected demand conditions (namely, ord_dom, ord_for and dem_exp) tends to reduce the probability of worsened credit conditions of about 1-3 percentage points. Finally, trade openness (opn) is found to have a statistically negative impact, suggesting that firms located in relatively more open regions (and thus more oriented to foreign competition) tend to exhibit better access to external finance. Overall, the evidence from the ape's relative to the level effects yields to similar conclusions, with magnitudes typically larger than the corresponding shock effects; the only exception is given by firm size (although the effect remains negative and statistically significant). Moreover, we find a remarkable similarity between the ape's for Pr($cre = 1$) and Pr($cre = 2$), suggesting that respondent firms tend to discriminate between worsening credit conditions vis-à-vis improving or stable conditions to access external sources of funding.

The ape's of the quarterly time dummies on Pr($cre = 3$) (the probability of a worsening in firms' self-reported assessment of their access to external credit) is plotted in Figure 1 (continuous black line) along with the 95 per cent confidence intervals (grey area). Interestingly, the evolution over time of the aggregate indicator of worsening access to external finance *conditional* on the individual level of creditworthiness of firms, $ape_t^{(RE)}$, signals two main spikes in correspondence of the two crisis periods included in the estimation sample, namely the global recession of 2008-2009 and the ensuing debt crisis of 2012-2014.

Figure 1

[4] As pointed out by Caporale et al. (2012), among others, the parameters of the linear regression model are similar to those for a probit model if the distances between the thresholds are nearly identical. In the present context, the fixed thresholds λ's in condition (3) are statistically significant at the 1 per cent level and different from one, indicating that the three ordinal categories are not equally spaced.

4. Deriving the credit crunch indicator

4.1 Matching supply and demand

Economic theory posits that credit squeezes generally arise as the result of asymmetric information between the borrower and the lender or because of exogenous factors like the implementation of more stringent regulatory rules. As for information asymmetry problems, borrowers may have incentives to withhold information when asking for credit. Lenders seek to tackle this issue by practicing screening (Allen, 1990) and monitoring (Rajan and Winton, 1995) so as to mitigate their exposure to counterparty risk. Besides controlling for the creditworthiness of borrowers, the identification of credit crunch episodes calls for controlling for banks' opportunity costs of providing risky loans (Bernanke and Lown, 1991) which is commonly epitomized by a measure of safe real interest rate. At the same time, it is well known that the implementation of some risk-based regulatory rules governing lenders' allocation of resources may have a significant negative impact on the supply of credit (Berger and Udell, 1994). The reduction in credit may thus coincide with banks having difficulties in meeting the minimum regulatory capital requirements in periods associated with a deterioration in asset quality (Pazarbasioglu, 1996). In particular, we use the real long-term interest rate (deflated by the annualized rate of change of the headline price index excluding energy, rlr_t, as in Holston et al., 2017, among others) as a proxy for changes in the banks' opportunity costs of providing risky loans. An increase in the safe real interest rate would make banks prone to invest more of their funds in risk-free assets, thus reducing the aggregate loan supply, *ceteris paribus* (Bernanke and Blinder, 1988). Hence, a positive relationship between rlr_t and $ape_t^{(RE)}$ is expected.

The relationship between the (perceived) credit availability and interest rates might also be affected by a contraction of the overall volume of credit available for the economy, regardless of the corporate borrowing rate on loans charged by banks. In keeping with this argumentation, financial intermediaries are expected to be reluctant in extending credit lines with compressed credit spread levels (defined as the difference between the corporate borrowing rate and the Euribor rate, csp_t). Accordingly, we include that measure of credit spread to control for potential macroeconomic effects on the estimated $ape_t^{(RE)}$ indicator. The assumption that banks are more willing to lend as the margins on corporate borrowing rate increase implies an expected negative relationship with the dependent variable. Moreover, we have also included a more direct control for the overall level loan demand of enterprises by resorting to the index of loan demand (ild_t) from the Bank Lending Survey carried by Bank of Italy. As an increase of ild_t signals a rise in the maximum amount which enterprises are entitled to borrow (in the form of either new credit lines or credit lines previously granted but not yet used) from the banking sector at any given time, an inverse relationship between ild_t and the evolution of $ape_t^{(RE)}$ is expected to hold.

Following Rottmann and Wollmershauser (2013), we derive an indicator of credit crunch by regressing the indicator capturing a worsening in the access to external funds conditional on the individual level of creditworthiness of firms, $ape_t^{(RE)}$ reported in Figure 1, on the above discussed controls. In other words, we take the ape of τ_t in equation (3), whose estimates are reported in Table (2) Equation (3), and regress on: long term interest rate, rlr_t, a measure of credit spread,

csp_t, and on the loan demand index, ild_t. The residual term of this second stage regression, cci_t, is likely to capture the mismatch between firms' appraisal of banks' lending policies and their determinants from the demand side. The resulting mismatch between supply and demand is expected to measure the degree of credit squeeze prevailing in the economy at a certain period t. Owing to the limited temporal extension of our estimation sample, we distil the information content conveyed by the candidate explanatory variables into a synthetic indicator by following a “nonmodel based” aggregation scheme as discussed in Marcellino (2006). Specifically, rlr_t, as well as csp_t and ild_t (with the inverted sign) are standardised so as to have zero mean and unit standard deviation. This step helps avoiding that the resulting (simple) average index of demand factors (idx_t), which is calculated in the subsequent step, is dominated by variables with a particularly pronounced degree of volatility and/or an incomparably high absolute mean.

4.2 Estimation results

Estimation results from a standard linear regression model

$$E[ape_t^{(RE)}] = \phi_0 + \phi_1 trnd + \phi_2 idx_t \tag{6}$$

are reported in Table 3 (Equation A.), where the deterministic component includes an intercept and a linear trend ($trnd$). We document a positive relationship between the response variable and the synthetic indicator idx_t: the estimated parameter is statistically significant at the 1 per cent nominal level of significance (or even better) according to the corresponding heteroskedasticity and autocorrelation consistent standard errors as devised by Newey and West (1987). Moreover, the linear regression is able to explain about three-fourth of the temporal variation of firms' perception of a restrictive banks' willingness to lend. For comparison purposes, we also report the estimation results for the regressions of the response variable on each standardized individual component of our synthetic supply index (Equation B., C., and D., respectively). Overall the results from these alternative specifications turn out be less satisfactory in terms of both log-likelihood and adjusted R-square with respect to our preferred specification (Equation A.), giving support to the choice of using a synthetic supply factor measure rather than a specific individual component of idx_t.

Table 3

As in Rottmann and Wollmershauser (2013), the residual term from the regression given by Equation (6), cci_t, that is the distance between the observed value of $ape_t^{(RE)}$ and its predicted value, can be interpreted as loan supply shocks. Specifically, the more positive the contribution of loan supply shocks to the firms' perception of a restrictive willingness to lend, *ceteris paribus,* the higher the probability that the economy is affected by a credit squeeze. On the other hand, negative values of cci_t would signal relatively favourable credit conditions, while the residual is expected to be zero in equilibrium. In order to ease economic interpretability, we project cci_t onto the [0,1] interval according to the following monotonic transformation: $\widetilde{cci}_t \equiv (\tanh(cci_t) + 1)/2$, where $\tanh(.)$ stands for the hyperbolic tangent function, which plots the transformed values in the [-1,+1] interval. It is worth noticing that the proposed transformation makes $\widetilde{cci}_t$'s readings comparable to those of popularly monitored diffusion indexes like the Purchasing Manager Index (PMI) series, with the value of 0.5 representing the critical threshold to discriminate between periods of credit squeeze ($cci_t > 0$) and those when credit constraints are not binding ($cci_t < 0$)[5]. Given the latent character of the concept of credit crunch, there is no track record of "known" credit squeeze in the past. One can therefore only inquire whether an indicators' evolvement is plausible. As Figure 2 shows, the $\widetilde{cci}_t$ indicator flags the global recession of 2008-2009 as the most severe episode of credit crunch experienced by the Italian economy over the last decade (with a peak of 0.57 in 2008q4). In the ensuing mild recovery, the loan supply of banks was laxer until the second recessionary episode in 2012-2014 related to the eruption of the sovereign debt crisis and the subsequent fiscal policy measures that compressed domestic demand. In the most recent period, dominated by the unconventional monetary interventions by ECB, the indicator is found to stand far away from its maxima. This evidence suggests that banks' willingness to lend was perceived as relatively accommodating although traces of less favourable credit conditions emerge at the very end of the sample when macroeconomic conditions have shown signs of slackening.

Figure 2

4.3 Using the credit crunch indicator for scenario analyses

In an effort to sharpen our understanding of how macroeconomic developments affect credit availability in the economy, this Section presents a scenario analysis to assess the extent to which factors like economic growth, the stance of monetary policy or the domestic money supply, as well as the quality of banks' balance sheet may influence the evolvement over time of the proposed credit crunch indicator (see, among others, Laker, 1999).

Operatively, $\widetilde{cci}_t$ is modelled as a function of: (a) the log-level of GDP (in first differences), q_t^{gdp}; (b) the short-term euro repo rate, q_t^{shr}; (c) the share of credit supply to the manufacturing sector over the overall lending to the private sector, q_t^{man}; (d) the growth rate of bad debts of non-financial corporations, q_t^{npl}. The estimation exercise is performed under realistic data-availability conditions so that the current values of our credit crunch indicator are regressed on lagged values of the explanatory variables in order to cope with the publication calendar of the series involved in the regression (Leduc and Sill, 2013; Girardi, 2014). Specifically, the estimation sample covers the period from 2008q2 to 2018q2. The latest available information for our credit crunch indicator is available around two weeks after the end of the quarter of reference (when the first quarter's Bank Lending Survey release is disseminated). At that date, we have information on the evolution of GDP up to the previous calendar quarter; likewise, quarterly figures for credit supply and non-performing loans (NPL) reflect lagged data availability, while contemporaneous data on interest

[5] The chosen monotonic transformation yields virtually identical results to the logit function, $\left[\frac{1}{1+\exp(-cci_t)}\right]$, while it looks preferable to alternative like those based on the standardized normal distribution $\Phi(cci_t/sd_{cci})$, where sd_{cci} indicates the sample standard deviation of cci_t, or the normalization $(cci_t - cci_{\min})/(cci_{\max} - cci_{\min})$, where $cci_{\min}$ and $cci_{\max}$ denote the sample minimum and maximum value, respectively, because it turns out to be less dependent on possible outliers in the sample.

rates may be used. Table 4 presents summary statistics of the observable market characteristics in our sample.

Table 4

As Table 4 shows $\widetilde{cci}_t$ is constrained by construction within the interval between 0 and 1. Because of the bounded nature of the dependent variable, we cannot implement an ordinary least squares (OLS) regression,

$$E(\widetilde{cci}_t|Q_t) = \theta_0 + \theta_1 q_t^{gdp} + \theta_2 q_t^{shr} + \theta_3 q_t^{man} + \theta_4 q_t^{npl} = Q_t\theta \quad (7)$$

since the predicted values from the OLS regression cannot be guaranteed to lie in the unit interval[6]. An alternative to the standard OLS specification is $E(\widetilde{cci}_t|Q_t) = G(Q_t\theta)$ where $G(.)$ satisfies $0 < G(z) < 1$, for all $z \in \Re$, ensuring that the predicted $\widetilde{cci}_t$ lies in [0, 1] interval. The most common functional forms for $G(.)$ are the standard cumulative normal distribution (i.e. the fractional-probit model case) and the logistic function (i.e. the fractional-logit model case)[7]. Given the non-linearity of the functions $G(Q_t\theta)$, the partial effects of the explanatory variables on $\widetilde{cci}_t$ are not constant, in contrast to the standard OLS case. Table 5 reports the ape's relative to both specifications (fractional-logit and fractional-probit regression models).

Table 5

The estimation results show a negative and statistically significant effect of GDP growth and (relative) credit availability for the manufacturing sector on the dependent variable, while rising interest rates or a worsening of the quality of banking balance sheets tend to increase the likelihood of experimenting a credit squeeze. Specifically, a GDP increase of 1 per cent is expected to reduce the level of the indicator of 1.6 percentage points. The magnitude (in absolute terms) of the ape's relative to the short interest rate and the share of loans in manufacturing over the total private sector turn out to be broadly similar (+2.6 and -2.2 percentage points, respectively), while a less relevant effect emerges for the dynamics of bad loans. All in all, both the fractional-logit and fractional-probit model specifications are able to capture about 60 per cent of the overall deviance of the response variable, with the GDP dynamics being by far the most relevant determinant of credit squeeze, as the decomposition of the explained deviance shows.

To assess how the predicted $\widetilde{cci}_t$ varies over the business cycle, we present in Figure 3 (Panel A.) a simulation exercise (based on the fractional-logit regression model) where the response predictions $E(\widetilde{cci}_t|Q_t)$ are computed under the assumption that GDP growth moves progressively from its maximum (corresponding to quarterly growth rate of about +1.1 per cent) to its minimum (corresponding to roughly -2.8 per cent), by keeping the remaining regressors fixed to their sample averages. The bold squares plot the resulting partial effects, while the grey lines identify the amplitude of the corresponding 95 per cent confidence region. The reported evidence is largely consistent with the idea that a relatively favorable economic environment tends to lower the

[6] See, among others, Bastos (2010) and Caporale and Girardi (2013) for a similar application of fraction regression models.

[7] Note that with the identity function the fraction regression model collapses to the standard OLS regression. The quasi-maximum likelihood estimator of θ in condition (7) is consistent regardless of the distribution of $\widetilde{cci}$ conditional on the Q's (Papke and Wooldridge, 1996).

counterparty risk, thereby making banks more inclined to extend loans. During boom times, firms (as well as households) are likely to commit larger proportions of their income flows to debt servicing, thus establishing a counter-cyclical relationship between credit squeeze and economic activity dynamics (Lowe and Rohling 1993).

Figure 3

In Panel B., C. and D. of Figure 3 we replicate the same exercise, by moving the interest rate, the share of total loans to the manufacturing sector, and the NPL dynamics, alternatively. The effects exerted by variables proxying the stance of monetary policy (the short-term interest rate) and the degree of (sector) credit availability (the ratio of loans to the manufacturing sector over the total loans to the private sector) on the response variable are largely consistent with both the bank lending and the balance sheet channels of monetary policy transmission, as Panel B. and Panel C. of Figure 3 show[8]. In both cases, worsened monetary and credit conditions (corresponding to interest rate increases and manufacturing to total loans ratio decreases, respectively) tend to affect negatively the aggregate loan supply and thereby favoring the occurrence of credit squeeze episodes. At the same time, the supply of credit may be crucially affected by the level of bad loans in the economy. Panel D. documents that the degree of credit squeeze gets progressively more severe when the degree of credit quality tends to deteriorate. This finding is in line with the idea that an increased NPL burden implies higher risk weights on bank loan portfolios in the calculation of regulatory capital ratios. Consequently, banks are likely to reduce the size of their balance sheet to cope with increased risk weights and capital absorption, eventually leading to a decline in loan supply (Froot and Stein, 1998; Van den Heuvel, 2008).

5. Extensions

5.1 Logit-FE and linear-TSLS specifications

So far, we have controlled for unobserved heterogeneity by introducing long-term averages of firm-level variables in the RE-OPM because, within a panel data Fixed Effect OPM (FE-OPM), there is no way to solve the incidental parameter problem and the cut-off parameters cannot be distinguished from the fixed effect parameters (identification problem). A possible alternative to the specification based on Wooldridge (2002) builds on the dichotomization of the ordered responses so as to apply the logit fixed effect (logit-FE) model proposed by Chamberlain (1980). We argue that the logit-FE specification is well-suited for the issue at stake in the light of the evidence of a clear dichotomous pattern as discussed in Section 3.2. Accordingly, we have

[8] Specifically, the bank lending channel operates through banks' liability side. It posits that a monetary contraction, by draining reserves from the banking system, tends to leave banks with fewer loanable funds, thereby reducing lending (Bernanke and Blinder 1988). At the same time, a less accommodative monetary policy increases banks' external finance premium pushing banks to respond by reducing the total amount of credit they are willing to supply (Stein 1998). When considering the balance sheet channel, a tight monetary policy operates through banks' asset side by reducing the net worth of borrowers with weaker fundamentals (Bernanke et al, 1996; Bernanke and Gertler 1989). Furthermore, a less accommodative monetary stance tends to increase the real value that banks must pay to retain deposits, which causes banks to fund fewer long-term projects (Diamond and Rajan, 2006).

generated a dummy variable $\underline{cre}_{j,l,s,t}$ taking value of 0, if $cre_{j,l,s,t} = 1$ or $cre_{j,l,s,t} = 2$, and 1, if $cre_{j,l,s,t} = 3$.

It is worth noticing that the logit-FE framework does not solve the issue related to the potential simultaneity between the dependent variable (firms' appraisal of the access to external finance) and the right-hand side regressors. In our context, the problem looks quite complex because of the discrete (or limited) nature of both the dependent and the independent endogenous variables. Luckily, the seminal work by Angrist (2001) has shown that in the case of a discrete (or limited) dependent variable the ape's can be consistently estimated by means of a linear two stage least squares (linear-TSLS). This result holds true even when the discrete or limited endogenous regressors are concerned because only the OLS estimation of the first-stage is guaranteed to produce first-stage residuals that are uncorrelated with fitted values and covariates. When the model is not correctly specified, indeed, the prediction of a nonlinear first-stage (like the one based on logit or probit models) can yield to inconsistent estimates. Accordingly, a nonlinear first-stage is not necessary, or even not desirable, to the point that is called as the "forbidden regression" (Angrist and Pischke 2009, p. 143).

In operative terms, we have regressed $\underline{cre}_{j,l,s,t}$ on the same set of explanatory variables as in the logit-FE regression equation, instrumenting the potentially endogenous variable, the $x_{j,l,s,t}$'s (i.e. from $empl$ to dom_exp_2 in Table 1) with each first lag, plus the second lag for liq_1 . The choice of the instruments is motivated by the fact that $x_{j,l,s,t-1}$ is correlated with $x_{j,l,s,t}$, and the second order lag has been included in order to make computable the Sargan-J statistic, checking for the quality of the entire set of instruments[9]. To assess the relevance of the instruments, we report in Table 6 the correlation between each potentially endogenous variable $x_{j,l,s,t}$ with its own instrument, $x_{j,l,s,t-1}$ (as well as $x_{j,l,s,t-2}$ for the case of liq_1). As the Table shows, each $x_{j,l,s,t}$ is strongly correlated with its lag $x_{j,l,s,t-1}$ and the same holds true for liq_1_{t-2} with liq_1_t, validating the relevance of the instruments.

Table 6

The second step regression is reported in Table 7 along with some additional tests about the quality of the estimates. The Sargan-J does not reject the null of validity of the instruments at the usual confidence levels (p-value of 0.28); both the tests for weak- and under-identification reject the null hypothesis, while the F-test rejects the null of irrelevance of the entire set of regressors.

Table 7

[9] Since a large number of instruments can overfit the instrumented variables, leading to inaccurate estimations and wrong inference in the Sargan-J test (Roodman, 2009) we have kept the number of over-identifying restrictions to its minimum, i.e. one. For this reason, only one second order lag has been included in the set of regressors.

5.2 Credit squeeze and macroeconomic fundamentals: a re-assessment

Before using $\underline{cre}_{j,l,s,t}$ as a dependent variable in a model matching supply and demand of banking loans, we must assess whether it can be considered as a valid proxy for credit constraint perceived by firms, so that collapsing answers one and two into a single one does not engender losses of useful information. As an initial step, we have plotted in Figure 4 the ape's of the time dummies of the baseline Generalized RE-OPM specification ($ape_t^{(RE)}$, continuous black line) against those from the logit-FE alternative ($ape_t^{(FE)}$, dashed line). The two series show very similar dynamics (correlation coefficient of 0.96), suggesting that no relevant information is wasted. A similar result is obtained when considering the temporal evolution of the ape's relative to the temporal dummies for the linear-TSLS specification ($ape_t^{(TSLS)}$, dotted line), which shows a degree of association with its baseline counterpart of about 95 per cent.

Figure 4

Against this backdrop, we have re-estimated equation (6) by using $ape_t^{(FE)}$ and $ape_t^{(TSLS)}$ in place of $ape_t^{(RE)}$, alternatively. Estimation results are reported in Table 8, while Figure 5 plots the resulting residual terms of the regression that have been normalised as detailed in Section 4.2 (dashed and dotted lines, respectively). In both cases, the credit crunch indicator is found to be at its height during the quarters of the 2008-2009 recession. Subsequently, a temporary retracement of the indicator can be detected until the eruption of the 2012-2014 debt crisis. After then, the degree of credit squeeze prevailing in the Italian economy turns out to be comfortably below the peaks occurred in the occurrence of the two recessionary episodes, pointing to a relatively positive firms' appraisal of their access to banking loans.

Table 8

Figure 5

As a final step of our robustness check, we have replicated the scenario analysis discussed in Section 4.3. Specifically, model (7) has been estimated by regressing, alternatively, the (standardised) residuals of the logit-FE and the linear-TSLS specifications on the same set of covariates (namely, GDP growth, the short-term euro repo rate, changes of the share of credit supply to the manufacturing sector over the overall lending to the private sector and the growth rate of bad debts of non-financial corporations), with the ape's (computed from a fractional-logit specification) are reported in Table 9[10]. Overall, we find confirmation of the sign of the ape's discussed in Section 4.3, although the goodness of fit measure tends to be slightly smaller than the share of explained deviance for the baseline specification. Nonetheless, GDP growth remains the most relevant factor when explaining the temporal evolution of the credit squeeze measure.

Table 9

[10] For the sake of brevity, we do not report the empirical evidence from the fractional-probit alternative. The estimated ape's as well as the conclusions from the scenario analysis exercises are virtually identical to those reported in the main text. The complete set of results is available from the authors upon request.

Panel A. and Panel B. of Figure 6 plot how the response variable varies when each predictor moves progressively from its maximum to its minimum by keeping the remaining regressors fixed to their sample averages. As in Figure 3, the bold squares indicate the resulting partial effects, while the grey lines refer to the amplitude of the corresponding 95 per cent confidence region. In both Panels, the upper left graph confirms the existence of a clear counter-cyclical relationship between credit crunch and economic activity dynamics. In contrast, the degree of credit squeeze gets progressively more severe when stance of monetary policy gets progressively more restrictive (the short-term interest rate, upper right graph) or when the amount of (sector) credit availability (the ratio of loans to the manufacturing sector over the total loans to the private sector, lower left graph) tends to decline.

Figure 6

6. Concluding remarks

This work presents a credit crunch indicator for the Italian economy by exploiting firm-level information drawn from a representative sample of manufacturing firms over the years from 2008 to 2018. The proposed empirical procedure consists in two main steps. Firstly, we apply nonlinear discrete outcome panel-data model to regress the responses to firms' assessment about the access to credit on a large set of observable firm-specific and regional characteristics. The regression model also allows for a set of quarterly time dummies whose estimated coefficients are interpreted as (unobserved) factors determining banks' loan supply once structural characteristics of the borrowers have been controlled for. Subsequently, the temporal profile of the stance of the bank lending policies perceived by firms has been regressed on a synthetic indicator that distils information relative to loan demand factors, including proxies for banks’ opportunity costs of providing risky loans. The residuals of this second-stage are thus interpreted as shifts of the loan supply curve: the more positive the contribution of the residual term to the firms’ perception of a restrictive willingness to lend, the higher the likelihood that the economy has experienced an episode of credit crunch.

The empirical evidence shows that the probability of credit crunch episodes lowers during periods of sustained economic growth and or when credit availability for the manufacturing sector is relatively abundant. In contrast, rising interest rates or a worsening of the quality of banking balance sheets tend to increase the likelihood of experimenting a credit squeeze. We also document that these results are robust to a number of alternative specifications and estimation techniques. From an operative viewpoint, the proposed methodology relies on timely available data, so that it might have useful applications for institutional purposes and policy analyses.

Admittedly, no attempt has been made in this paper to investigate whether and to what extent the severity of credit crunch has affected in an asymmetric way large and small-medium enterprises or firms located in the Centre-North with respect to those operating in Southern regions. In this respect, further research would be desirable by splitting the sample according to firm employment, as in Criscuolo et al. (2012), or to the spatial location of the productive units, as proposed in Basile et al. (2014). These issues are beyond the scope of the present study, and will be the subject of future research.

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Appendix

Our analysis uses data collected within the Joint Harmonised EU Programme of Business and Consumer Surveys, which inquires every month about 120,000 enterprises, as well as 40,000 consumers, across Europe (see European Commission, 2017). As for the business sectors, enterprises are asked to assess the development of concepts like production, order books, or employment. Data are typically qualitative in nature, in the sense that they convey firms' opinions - rather than quantitative information - on production, demand, inventories and other variables relevant at the firm level. Questions usually ask the firm to choose among three possible answers arranged on a Likert scale. As for the temporal horizon, survey questions refer to the present situation, developments over the past three months or expectations for the next three months. Table A.1 reports the questions of the manufacturing survey and the associated firm-specific variables that have been used in the empirical analysis.

Table A.1 - Survey questions

Variable	Definition	Survey question
emp	Number of employees (quantitative question)	What is the number of employees in the current month?
liq	Liquidity (level), with respect to operational needs	In comparison with the previous month, do you consider the current level of your liquidity conditions as *good*, *mediocre* or *bad*?
liq_fwd	Liquidity (level), next 3 months	Do you expect your liquidity conditions to *improve*, *remain unchanged* or *deteriorate* over the next three months?
exp	Export turnover ratio (quantitative question)	What is the export turnover ratio (in percentage terms) in the current quarter?
ord_dom	Domestic order books (level), current	Excluding seasonal changes, do you consider the current level of your domestic order book as *high, normal* or *low*?
ord_for	Export order books (level), current	Excluding seasonal changes, do you consider the current level of your export order book as *high*, *normal* or *low*?
dem_exp	Total order books (level), next 3 months	Do you expect your total order books to *increase*, *remain unchanged* or *decrease* over the next three months?

For the case of Italy, the National Institute of Statistics (ISTAT) collects information in the form of panels stratified by geographical location, sector and size. Respondents are extracted from the official register of active firms. As for the manufacturing sector, the samples size is about 4,000 firms. Interviews are conducted through Computer Assisted Telephone Interviewing (CATI) in the first two weeks of each month and the results are typically published before the end of the reference month and not revised afterwards.

Since March 2008, a specific section focusing on the bank-firm relationship has been added to the manufacturing survey in order to collect some information about credit access conditions.

Specifically, firms are asked to report their perceptions on credit conditions, with three possible answers arranged on a Likert scale (getting better, stable, getting worse). This question corresponds to the variable discussed in Section 2.1. Subsequently, firms have to indicate whether or not their appraisal is based on a formal contact with a credit institution.

If it is the case, respondents are asked to specify whether:

a) their request for credit has been obtained at the same conditions as three months before;
b) their request for credit has been obtained at worsening conditions.

   If it is the case, a question is additionally asked about its determinants by allowing for the following possible answers: (a) higher interest rates, (b) higher collateral (real or personal guarantees), (c) limits to the amount of loans, (d) higher costs;

c) their request for credit has been denied.

   If it is the case, a question is additionally asked about whether credit is due to (a) an explicit denial by the financial institution or (b) withdraw by the firm due to excessively unfavorable conditions imposed by the financial institution;

d) the contact with the bank was only motivated by a request of information.

Tables

Table 1 – Ordered probit estimation results

	(A) Pooled-OPM		(B) RE-OPM		(C) Generalized RE-OPM *Equation 1*		*Equation 2*	
	Shock effect	Level effect	Shock effect	Level effect	Shock Effect	Level effect	Shock effect	Level effect
emp	0.047***	-0.007**	-0.046**	-0.012**	-0.046**	-0.013**	-0.046**	-0.013**
	(0.016)	(0.003)	(0.018)	(0.006)	(0.018)	(0.006)	(0.018)	(0.006)
liq_1	0.546***	-0.953***	0.598***	1.160***	-0.598***	-1.159***	-0.598***	-1.159***
	(0.015)	(0.019)	(0.016)	(0.039)	(0.016)	(0.039)	(0.016)	(0.039)
liq_2	0.391***	-0.700***	0.428***	0.799***	-0.428***	-0.799***	-0.428***	-0.799***
	(0.013)	(0.019)	(0.013)	(0.040)	(0.013)	(0.040)	(0.013)	(0.040)
liq_fwd_1	0.428***	-1.011***	0.465***	1.208***	-0.465***	-1.206***	-0.465***	-1.206***
	(0.016)	(0.038)	(0.016)	(0.080)	(0.016)	(0.079)	(0.016)	(0.080)
liq_fwd_2	0.281***	-0.551***	0.315***	0.677***	-0.315***	-0.676***	-0.315***	-0.676***
	(0.011)	(0.025)	(0.011)	(0.060)	(0.011)	(0.060)	(0.011)	(0.060)
exp	-0.000	-0.000	-0.000	-0.000	-0.001*	-0.001*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ord_dom_1	0.094***	-0.310***	0.101***	0.418***	-0.101***	-0.419***	-0.101***	-0.419***
	(0.017)	(0.038)	(0.017)	(0.076)	(0.017)	(0.076)	(0.017)	(0.080)
ord_dom_2	0.077***	-0.089***	0.085***	-0.080*	-0.085***	-0.080*	-0.085***	-0.080*
	(0.010)	(0.020)	(0.010)	(0.044)	(0.010)	(0.044)	(0.010)	(0.044)
ord_for_1	0.078***	-0.108***	0.088***	-0.128**	-0.088***	-0.131**	-0.088***	-0.131**
	(0.015)	(0.031)	(0.015)	(0.058)	(0.015)	(0.058)	(0.015)	(0.058)
ord_for_2	0.034***	0.012	0.043***	-0.035	-0.043***	-0.036	-0.043***	-0.036
	(0.010)	(0.020)	(0.010)	(0.038)	(0.010)	(0.038)	(0.010)	(0.038)
dem_exp_1	0.129***	-0.277***	0.147***	0.230***	-0.147***	-0.229***	-0.147***	-0.229***
	(0.013)	(0.034)	(0.013)	(0.074)	(0.013)	(0.074)	(0.013)	(0.074)
dem_exp_2	0.089***	-0.266***	0.102***	0.203***	-0.102***	-0.203***	-0.102***	-0.203***
	(0.011)	(0.031)	(0.011)	(0.067)	(0.011)	(0.067)	(0.011)	(0.066)
bwd	0.016***		0.023*		0.048***		0.011	
	(0.006)		(0.013)		(0.016)		(0.014)	
ius	0.018***		0.002		-0.020**		0.011	
	(0.004)		(0.007)		(0.009)		(0.008)	
opn	-0.053***		-0.090**		-0.135***		-0.073*	
	(0.018)		(0.040)		(0.048)		(0.042)	
qlp	-0.160		0.039		0.056		0.040	
	(0.147)		(0.286)		(0.359)		(0.306)	
Obs	163,077		163,077		163,077			
LL	-111,557		-102,703.62		-102,683.38			
χ^2	[0.000]		[0.000]		[0.000]			
AIC	223,300.3		205,576.3		205,565.3			
BIC	224,230.5		206,516.5		206,545.5			
$\chi^2 - PRA$								

Note. As detailed in Section 2.1, the dependent variable is given by firms' appraisal of the credit condition(cre). Time dummies, albeit included among the regressors, are omitted for ease of exposition. Standard errors are in parentheses. Single, double and triple stars indicate significance at the 10, 5 and 1 percent levels, respectively. Obs indicates the number of observations. χ^2 is the test statistics for the hypothesis of null joint impact of covariates on the dependent variable. LL, AIC and BIC indicate the value of the log-likelihood function, the Akaike Information Criterion, and the Bayesian Information Criterion, respectively. $\chi^2 - PRA$ is the test statistics for symmetric impact of the covariates on the dependent variable across categories, with the p-value in square brackets. Firm-specific regressors and regional characteristics are defined in Section 2.2 and 2.3, respectively.

Table 2 – Average Probability Effects

	Equation 1		Equation 2		Equation 3	
	Shock effect	Level effect	Shock effect	Level effect	Shock effect	Level effect
emp	0.538**	0.156**	0.476**	0.138**	-1.013**	-0.293**
	(0.216)	(0.0726)	(0.191)	(0.0640)	(0.406)	(0.137)
liq_1	7.050***	13.67***	6.242***	12.11***	-13.29***	-25.78***
	(0.195)	(0.487)	(0.201)	(0.429)	(0.348)	(0.838)
liq_2	5.052***	9.431***	4.473***	8.350***	-9.525***	-17.78***
	(0.155)	(0.487)	(0.154)	(0.414)	(0.278)	(0.864)
liq_fwd_1	5.486***	14.23***	4.857***	12.60***	-10.34***	-26.82***
	(0.192)	(0.941)	(0.188)	(0.859)	(0.350)	(1.759)
liq_fwd_2	3.721***	7.970***	3.294***	7.056***	-7.015***	-15.03***
	(0.130)	(0.713)	(0.126)	(0.630)	(0.236)	(1.326)
exp	0.00150	0.00255	0.00133	0.00226	-0.00283	-0.00481
	(0.00280)	(0.00386)	(0.00248)	(0.00341)	(0.00529)	(0.00727)
ord_dom_1	1.192***	4.946***	1.055***	4.379***	-2.247***	-9.326***
	(0.203)	(0.892)	(0.180)	(0.796)	(0.382)	(1.683)
ord_dom_2	1.003***	0.938*	0.888***	0.831*	-1.892***	-1.769*
	(0.116)	(0.518)	(0.104)	(0.460)	(0.219)	(0.978)
ord_for_1	1.040***	1.544**	0.920***	1.367**	-1.960***	-2.911**
	(0.178)	(0.684)	(0.158)	(0.609)	(0.335)	(1.292)
ord_for_2	0.504***	0.419	0.446***	0.371	-0.950***	-0.790
	(0.120)	(0.447)	(0.107)	(0.396)	(0.227)	(0.842)
dem_exp_1	1.739***	2.704***	1.540***	2.394***	-3.279***	-5.097***
	(0.155)	(0.869)	(0.140)	(0.768)	(0.292)	(1.635)
dem_exp_2	1.203***	2.398***	1.065***	2.123***	-2.267***	-4.522***
	(0.131)	(0.785)	(0.118)	(0.692)	(0.247)	(1.475)
bwd	-0.560***		0.277		0.283	
	(0.174)		(0.226)		(0.289)	
ius	0.194*		-0.518***		0.323*	
	(0.107)		(0.140)		(0.169)	
opn	1.171**		0.425		-1.596*	
	(0.536)		(0.704)		(0.890)	
qlp	1.785		2.503		-4.288	
	(4.156)		(5.628)		(6.760)	

Note. As detailed in Section 2.1, the dependent variable is given by firms' appraisal of the credit condition (cre). Average probability effects (ape's) are defined in Section 2.4. Values are multiplied by 100. Time dummies, albeit included among the regressors, are omitted for ease of exposition. Standard errors in parentheses. Single, double and triple stars indicate significance at the 10, 5 and 1 percent levels, respectively. Firm-specific regressors and regional characteristics are defined in Section 2.2 and 2.3, respectively.

Table 3 – Second stage regression

	Equation A.	Equation B.	Equation C.	Equation D.
$cnst$	1.715 (2.618)	0.663 (1.761)	3.386 (2.486)	4.646** (1.851)
$trnd$	-0.199** (0.094)	-0.121 (0.073)	-0.278*** (0.084)	-0.324*** (0.067)
idx_t	4.870*** (0.941)	.	.	.
rlr_t	.	4.552*** (0.741)	.	.
csp_t	.	.	-3.386*** (0.093)	.
ild_t	.	.	.	-2.910*** (0.652)
Obs	41	41	41	41
LL	-118.627	-121.023	-123.538	-125.950
R^2_{adj}	0.752	0.675	0.558	0.503

Note. As detailed in Section 3.2, the dependent variable is given by the average probability effects of the quarterly time dummies on Pr($cre = 3$), i.e. the probability of a worsening in firms' self-reported assessment of their access to external credit. The deterministic component is given by a time polynomial of order one, with $cnst$ and $trnd$ denoting the intercept and the linear trend, respectively. The regressors entering Equations A., B., C., and D. are defined in Section 4.1. Heteroskedasticity and autocorrelation consistent standard errors à la Newey and West (1987) are reported in parenthesis. Obs indicates the number of observations, while LL indicates the value of the log-likelihood function. R^2_{adj} is the adjusted coefficient of determination.

Table 4 – Credit crunch indicator and its determinants: descriptive statistics

	$\widetilde{cci}$	q^{gdp}	q^{shr}	q^{man}	q^{npl}
$Mean$	0.500	-0.112	0.777	-0.004	3.619
Min	0.465	-2.791	0.000	-0.817	-11.229
Max	0.569	1.104	4.250	0.451	20.366
$I\ Quartile$	0.486	-0.559	0.050	-0.167	0.977
$Median$	0.497	0.220	0.580	0.012	4.296
$III\ Quartile$	0.514	0.393	1.000	0.143	6.752

Note. As detailed in Section 4.2, $\widetilde{cci}$ refers to the proposed credit crunch indicator which is given by the [0,1] transformation of the regression residual from equation (6). As for its determinants, q^{gdp} denotes the first difference of the log-level of real GDP; q^{shr} is the short-term euro repo rate; q^{man} stands for the quarterly change of the share of credit supply to the manufacturing sector over the overall lending to the private sector; q^{npl} is the growth rates of bad debts of non-financial corporations (see also Section 4.3).

Table 5 – Average partial effects from fractional regression model estimates

		Fractional-logit	*Fractional-probit*
q^{gdp}		-0.016***	-0.016***
		(0.003)	(0.003)
q^{shr}		0.026***	0.026***
		(0.005)	(0.005)
q^{man}		-0.022***	-0.022***
		(0.008)	(0.008)
q^{npl}		0.001**	0.001**
		(0.000)	(0.000)
Deviance explained		0.603	0.601
Of which due to:	q^{gdp}	0.232	0.231
	q^{shr}	0.142	0.144
	q^{man}	0.102	0.102
	q^{npl}	0.127	0.124

Note. The conditional mean of the credit crunch indicator is computed as $E(\widetilde{cci}_t|Q_t) = G(Q_t\theta)$, where $G(.)$ is either the logistic function (column "Fractional-logit") or the standard cumulative normal distribution (column "Fractional-probit"). The estimated values refer to the average partial effects. Standard errors in parentheses. Single, double and triple stars indicate significance at the 10, 5 and 1 percent levels, respectively. See also Table 4.

Table 6 - First stages

	emp	liq_1	liq_2	liq_fwd_1	liq_fwd_2	exp	ord_dom_1	ord_dom_2	ord_for_1	ord_for_2	dem_exp_1	dem_exp_2
$x_{j,l,s,t-1}$	83.04***	29.20***	31.35***	16.71***	17.39***	77.07***	26.73***	25.62***	29.91***	24.42***	26.76***	17.09***
	(1.987)	(0.598)	(0.799)	(0.689)	(0.566)	(0.408)	(0.782)	(0.566)	(0.736)	(0.566)	(0.587)	(0.584)
$x_{j,l,s,t-2}$		17.71***										
		(0.491)										
Obs	120,894	120,894	120,894	120,894	120,894	120,894	120,894	120,894	120,894	120,894	120,894	120,894
$Number\ of\ firms$	6,518	6,518	6,518	6,518	6,518	6,518	6,518	6,518	6,518	6,518		6,518
R^2	0.995	0.894	0.289	0.176	0.0537	0.0693	0.132	0.189	0.205	0.123	0.0793	0.0283

Note. The Table reports the correlation between each endogenous variable $x_{j,l,s,t}$ with its own instrument, $x_{j,l,s,t-1}$ (as well as $x_{j,l,s,t-2}$ for the case of liq_1). Columns indicate the instrumented variable and the first row indicates the instrument, i.e. the corresponding first lag, $x_{j,l,s,t-1}$. The second row reports the second lag only for liq_1. Robust standard errors in parentheses. Values are multiplied by 100. Single, double and triple stars indicate significance at the 10, 5 and 1 percent levels, respectively. Other regressors, not reported for ease of exposition, are exactly the same as those reported in Table 7, i.e. firm-specific regressors, time dummies and regional characteristics, as defined in Section 2.2 and 2.3, respectively

Table 7 – Comparison between Logit and instrumental variable

	Logit-FE	Linear-TSLS
emp	-1.440*** (0.368)	0.244 (0.771)
liq_1	-8.564*** (1.932)	-25.24*** (1.599)
liq_2	-6.787*** (1.528)	-19.79*** (1.487)
liq_fwd_1	-5.344*** (1.230)	-18.50*** (3.023)
liq_fwd_2	-5.770*** (1.301)	-19.23*** (2.352)
exp	0.00340 (0.00479)	0.0218** (0.0103)
ord_dom_1	-1.398*** (0.488)	1.707 (1.936)
ord_dom_2	-1.759*** (0.439)	0.298 (1.366)
ord_for_1	-0.651* (0.350)	-2.846* (1.661)
ord_for_2	-0.892*** (0.283)	-2.652* (1.438)
dem_exp_1	-2.169*** (0.541)	-0.852 (1.959)
dem_exp_2	-1.968*** (0.480)	-1.140 (2.250)
bwd	0.929 (1.100)	-0.456 (1.477)
ius	-0.303 (0.548)	0.228 (0.886)
opn	-2.708 (3.057)	3.622 (5.071)
qlp	12.36 (21.54)	4.554 (34.05)
Obs	131,367	120,133
$P(F)$		0.00
$P(Under)$		0.00
$Weak\ id\ test\ (F)$		142.2
$P(Sargan - J)$		0.275

Note. The dependent variable is the binary dummy $\underline{cre}_{j,l,s,t}$ defined in Section 5.1. Ape's in column "Logit-FE", coefficients in column "Linear-TSLS", robust standard errors in parentheses. Values are multiplied by 100. Single, double and triple stars indicate significance at the 10, 5 and 1 percent levels, respectively. Firm-specific regressors and regional characteristics are defined in Section 2.2 and 2.3, respectively, time dummies, albeit included among the regressors, are omitted for ease of exposition. Obs indicates the number of observations; $P(F)$ represents the p-value of the joint F-test of no relevance of the entire set of regressors; $P(under)$ refers to the p-value of the null hypothesis of under-identification; $Weak\ id\ test\ (F)$ is the F-test of the null hypothesis of weak identification; $P(Sargan - J)$ is the p-value of the Sargan-J test of the null hypothesis of instrument validity.

Table 8 –Second stage regression: robustness

	Logit-FE	Linear-TSLS
$cnst$	2.596	3.594
	(2.08)	(2.247)
$trnd$	-0.288***	-0.299***
	(0.073)	(0.089)
idx_t	3.813***	4.027***
	(0.749)	(1.097)
Obs	41	41
LL	-119.781	-122.819
R^2_{adj}	0.709	0.544

Note. As detailed in Section 5.2, the dependent variable is given by the average probability effects of the quarterly time dummies from the estimates of the Logit-FE and the Linear-TSLS. The deterministic component is given by a time polynomial of order one, with $cnst$ and $trnd$ denoting the intercept and the linear trend, respectively, while idx is the index of demand factors presented in Section 4.1. Heteroskedasticity and autocorrelation consistent standard errors à la Newey and West (1987) are reported in parenthesis. Obs indicates the number of observations, while LL indicates the value of the log-likelihood function. R^2_{adj} is the adjusted coefficient of determination.

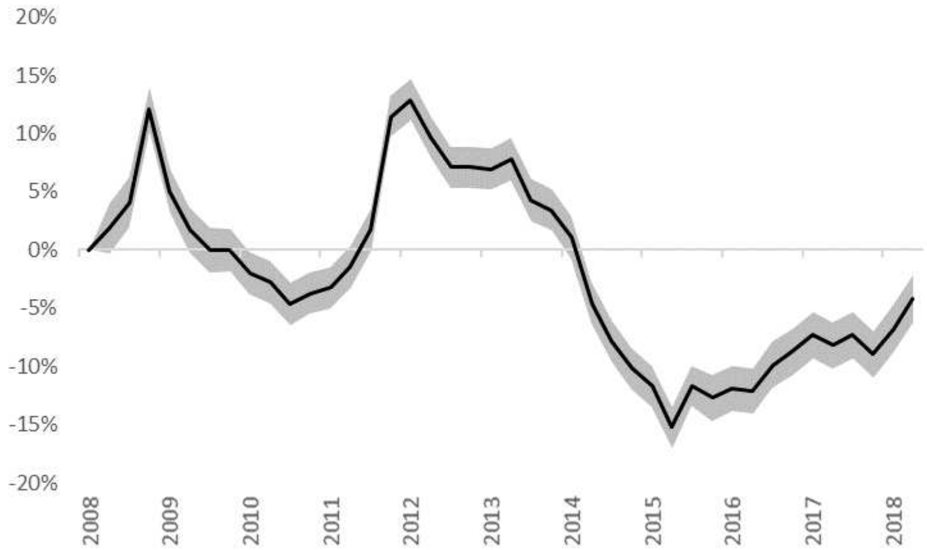
Table 9 – Average partial effects from fractional regression model estimates

		Logit-FE	Linear-TSLS
q^{gdp}		-0.018***	-0.028***
		(0.003)	(0.004)
q^{shr}		0.018***	0.031***
		(0.004)	(0.007)
q^{man}		-0.016***	-0.027***
		(0.007)	(0.010)
q^{npl}		0.001***	0.002***
		(0.000)	(0.001)
Deviance explained		0.497	0.644
Of which due to:	q^{gdp}	0.270	0.326
	q^{shr}	0.078	0.111
	q^{man}	0.076	0.105
	q^{npl}	0.073	0.102

Note. As detailed in Section 5.2, the dependent variable is given by the average probability effects of the quarterly time dummies from the estimates of the Logit-FE and the Linear-TSLS. The conditional mean of the credit crunch indicator is computed as $E(\widehat{cci}_t|Q_t) = G(Q_t\theta)$, where $G(.)$ is the logistic function. See also Table 4 and Table 5.

Figures

Figure 1 – Generalized RE-OPM estimation results: ape's of fixed time effects



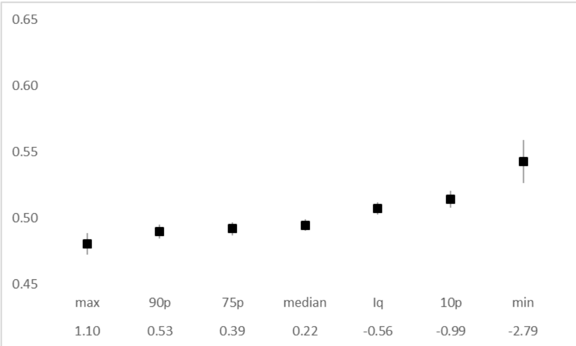
Note. The continuous black line represents the average probability effects of the quarterly time dummies on $\Pr(cre = 3)$, i.e. the probability of a worsening in firms' self-reported assessment of their access to external credit. The grey area identifies the 95 per cent confidence interval.

Figure 2 – Generalized RE-OPM estimation results: credit crunch indicator

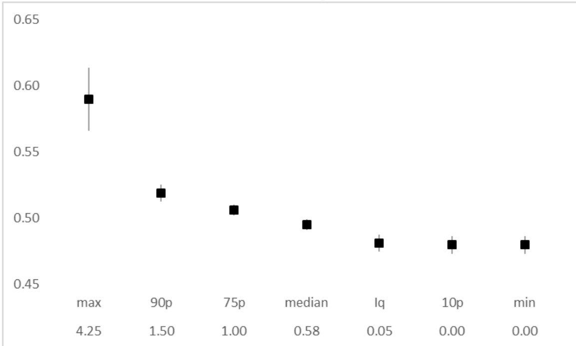
Note. The graph shows the normalised version of the residual term of the regression equation (6) as discussed in Section 4.2: the more positive (negative) the contribution of the residual term to the firms' perception of a restrictive willingness to lend, the higher (lower) the likelihood that the economy has experienced an episode of credit crunch. The value of 0.5 line identifies the critical threshold to discriminate between periods of credit squeeze and those when credit constraints are not binding.

Figure 3 – Generalized RE-OPM estimation results: scenario analysis

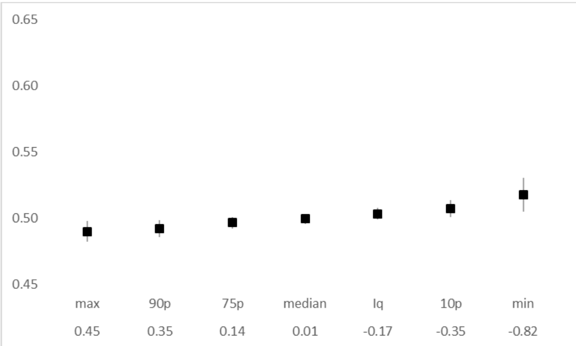
Panel A: q^{gdp}



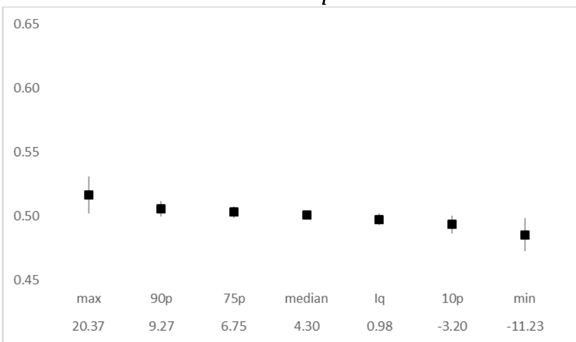
Panel B: q^{shr}



Panel C: q^{man}



Panel D: q^{npl}



Note. The bold squares indicate how the conditional mean $E(\widetilde{cci}_t|Q_t)$ varies when a given predictor in equation (6) moves progressively from its maximum to its minimum, by keeping the remaining regressors fixed to their sample averages. The simulation exercise is computed at selected sample values (namely, maximum, 90th percentile, third quartile, median, first quartile, 10th percentile, minimum). Vertical grey lines identify the amplitude of the corresponding 95 per cent confidence region. See also Table 4.

Figure 4 – Ape's of fixed time effects: evidence from Logit-FE and Linear-TSLS alternatives

Note. The continuous black line refers to the results for the baseline Generalized RE-OPM specification (and plotted in Figure 1), while the dashed and dotted lines are relative to the logit-FE and linear-TSLS alternatives, respectively.

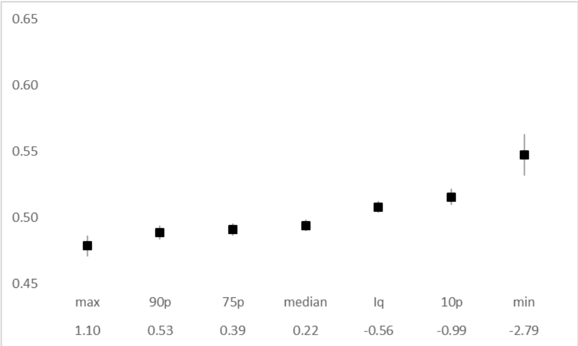
Figure 5 – Credit crunch indicator: evidence from Logit-FE and Linear-TSLS alternatives

Note. The continuous black line refers to the results for the baseline Generalized RE-OPM specification, while the dashed and dotted lines are relative to the logit-FE and linear-TSLS alternatives, respectively. See also Figure 2.

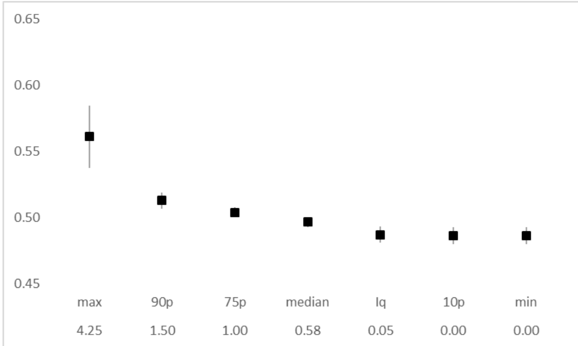
Figure 6 – Scenario analysis: evidence from Logit-FE and Linear-TSLS alternatives

I. Logit-FE specification

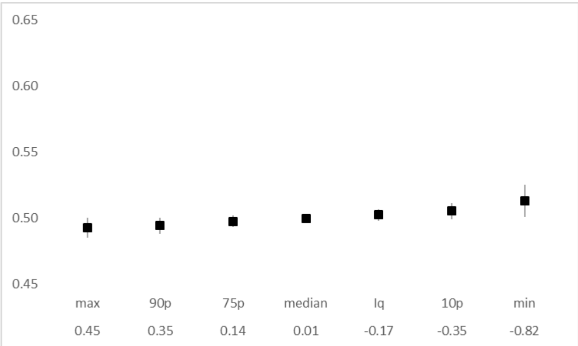
Panel A: x^{gdp}



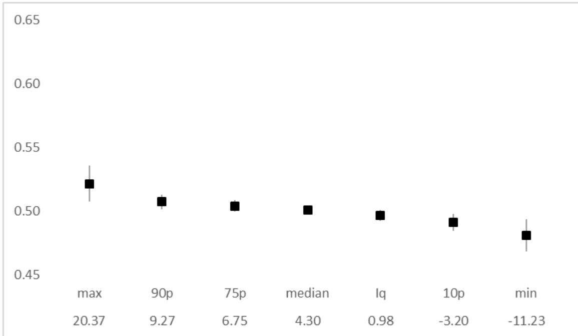
Panel B: x^{shr}



Panel C: x^{man}

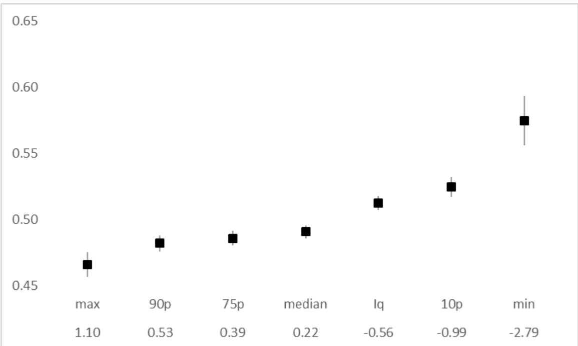


Panel D: x^{npl}

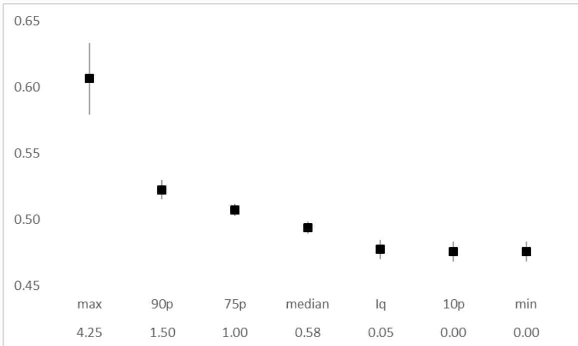


II. Linear-TSLS specification

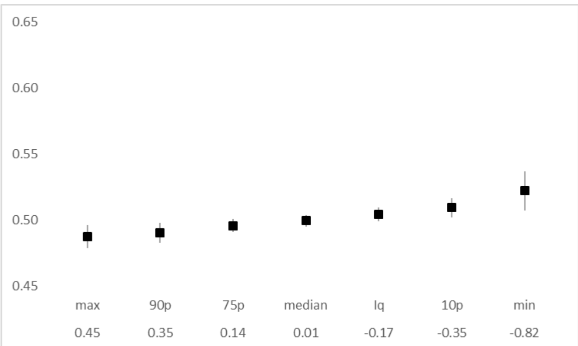
Panel A: x^{gdp}



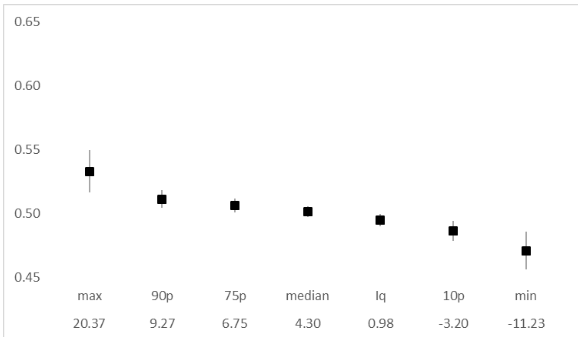
Panel B: x^{shr}



Panel C: x^{man}



Panel D: x^{npl}



Note. See Figure 3 and Table 4.