Assessing dynamics of credit supply and demand for French SMEs, an estimation based on the Bank Lending Survey[1]

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Credit supply and demand cannot be observed simultaneously as quantitative data do not enable to disentangle the two effects. Nevertheless, the Bank Lending Survey (BLS) conveys additional information on variations of credit standards for approving loans and credit demand perceived by banks.

In this study, credit supply and demand dynamics are estimated through a dynamic disequilibrium model relating balance of opinions from the BLS and flows of loans. Such a model applied on SMEs in France between 2006 and 2013 shows that credit supply fell sharply in 2008, but afterwards, flows have mainly been driven by SMEs' demand for credit.

[1] This article reflects the opinions of the authors and does not necessarily express the views of the Banque de France.

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Non-technical summary

The Bank Lending Survey (BLS), a qualitative survey led across the Eurosystem since 2003, is an additional source of information on credit markets. Every quarter, euro area bankers are asked about their opinions on the evolutions of credit standards and demand for different counterparts. Their individual answers are then gathered to produce macro-economic indicators reflecting credit market conditions in the euro area. Nevertheless, the BLS balances of opinions do not enable to disentangle properly credit supply and demand as they reflect evolutions, and not levels, of credit standards and credit demand perceived by bankers. Besides, evolutions of BLS indicators and actual credit market data may be difficult to relate.

This paper expands previous studies by proposing an original estimation method, which enables to disentangle and estimate, in quantitative terms, credit supply and demand levels. A dynamic disequilibrium model linking solely net credit flows and BLS balances of opinions, a model never applied to our knowledge on these data, is considered. Disequilibrium models are defined as models, for which supply and demand cannot be observed simultaneously; only their minimum is observable. In this study, actual net credit flows are supposed to match the minimum of credit supply and demand at each observation date. Besides, the model includes dynamic components, implying the use of an innovative estimation method. This model is applied to data on SMEs' credit in France. This is particularly meaningful as French SMEs rely heavily on banks as credit intermediaries.

From this model, indicators on credit supply and demand of SMEs have been extracted. Results are consistent with studies and surveys on access to credit for French SMEs. On one hand, SMEs may have been credit rationed during the financial crisis, but only moderately and transitorily. On the other hand, if credit demand from SMEs has significantly decreased during both Lehman Brothers and the sovereign debt crisis, the demand appears still sluggish in the aftermath. Those results have been obtained using a parsimonious model due to the small sample available. As time goes by, this model may be enriched with other variables. Besides, as a growing attention is put on granular data, a dynamic model applied at a micro level relying on bank's qualitative answers to the BLS questionnaire could be explored.

I. Introduction

1. Disentangling credit supply and credit demand

Credit developments in the last years have been followed closely by decisions makers but simultaneous deterioration of banks' balance sheets and firms demand made it more difficult to design the most appropriate policies. The balances of opinions from the Bank Lending Survey, a qualitative survey conducted since 2003 at the Eurozone level, complement in a qualitative manner the usual quantitative data such as credit flows, to enlarge the range of data available to economic analysis. Nevertheless, quantitative and qualitative data on credit still do not enable to disentangle rigorously credit supply and demand.

This paper contributes to this objective, by linking qualitative and quantitative data to simulate credit supply and demand paths. Credit supply and demand to French SMEs are estimated through a dynamic disequilibrium model relating balances of opinions from the Bank Lending Survey and net credit flows. This article contributes to different strands of the literature. Firstly, even though Bank Lending Survey balances of opinions have already been used to explain the evolution of credit flows, to our knowledge, a methodology such as a dynamic disequilibrium model has never been proposed. Besides, several articles on the credit market have used a disequilibrium model but in its static form. This study relies on a dynamic form that allows the current supply and demand components to depend on their past values. Finally, few articles take advantage of the Bank Lending Survey to analyze the credit distribution to SMEs. However, the SMEs, including microenterprises, represent in France more than 99% of the enterprises, more than 50% of the jobs and around 44% of the value added.[3] Besides, SMEs are strongly dependent on the bank financing. As a consequence, the evolutions of credit to SMEs should be monitored closely.

For this purpose, several surveys on credit access of SMEs have been set up in the last years. Nowadays, for most European countries, perceptions of both bankers and enterprises on credit markets are collected and analyzed. After the implementation of the Bank Lending Survey, the European Central Bank in collaboration with the European Commission has set up in 2009 the semi-annual survey SAFE dedicated to financing conditions faced by SMEs; enterprises are asked to report their requested external financing and the financing obtained. For France, the Banque de France has decided firstly to launch a monthly edition of the Bank Lending Survey as of 2012, in addition to the quarterly one conducted under the aegis of the ECB, and secondly to conduct its own survey on small and medium-sized enterprises and mid-tier enterprises to assess their demand for financing and the credits obtained with respect to demands.

2. The Bank Lending Survey

The *Bank Lending Survey* has been set up by the Eurosystem in 2003, in the manner of those already carried out by Japanese and American central banks since 2000

[3] Source: French National Institute of Statistics and Economic Studies (INSEE).

(*Senior Loan Officer Opinion Survey on Bank Lending Practices at Large Japanese Banks*) and 1967 (*Senior Loan Officer Opinion Survey on Bank Lending Practices)* respectively. This qualitative survey, implemented in each euro area country, has been developed to enhance monetary policy-makers' knowledge on credit markets.

Each quarter, senior loans officers are asked to assess evolutions of credit supply and credit demand for different counterparts. Additional information on those evolutions is also provided, such as the underlying causes of these variations (credit factors : balance sheet constraints, external financing costs, competitive pressure, and demand factors such as the weight of other types of financing) and how credit standards are modified (variations of margins and amounts granted). Depending on the economic and regulatory environment questions may be added temporarily.

Senior loans officers give their opinion on the evolutions of credit standards by choosing among five modalities: "tightened considerably", "tightened somewhat", "remained basically unchanged", "eased somewhat", and "eased considerably". Similarly, evolutions of credit demand are assessed by bankers who choose among five modalities: "decreased considerably", "decreased somewhat", "remained basically unchanged", "increased somewhat", or "increased considerably".

In France, each quarter, major banking institutions give their opinions on various markets segments: credit to large enterprises, credit to SMEs, consumer loans and loans for house purchases. For each question, a balance of opinions is calculated from individual responses. The indicator of the evolution of credit standards (resp. the evolution of credit demand) is defined as the difference between the percentages of weighted answers relating a tightening (resp. an increase) and those relating an easing (resp. a decrease). Each individual answer is weighted by bank weight within the sample. The sample is designed to represent the French banking system: the representativeness rate of the BLS reaches 54% of the outstanding amount of credits to enterprises, 86% for loans for house purchases and 58% for consumer loans.

Since 2007, The Banque de France has been experimenting a monthly version of the ECB's Bank Lending Survey. The monthly questionnaire resumes the principal questions of the quarterly one on evolutions of credit supply and credit demand for the different counterparts; but bankers are asked to assess monthly evolutions instead of estimating quarterly ones. Since 2012, as credit markets require a close monitoring, the monthly Bank Lending Survey is published every month.

3. Previous studies

The Bank Lending Survey provides additional information on credit markets, allowing to disentangle credit supply evolutions from credit demand ones. Econometric models such as macroeconomic models linking credit cycles, business cycles and monetary policy may take advantage of this original information. Ciccarelli et al. (2010) estimate the impact of a monetary policy shock on GDP and inflation through the credit channel in the US and the euro area. For this purpose, a VAR model including BLS balances of opinions on credit demand and supply to represent the balance sheet channel and the bank lending channel respectively is estimated. According to their results, households reduce their credit demand due to constraints on their balance sheets whereas businesses credits may more probably be affected by banks' reduction of credit supply.

Besides, BLS balances of opinions have been frequently used as explanatory variables of the evolutions of credit flows, and those of GDP (De Bondt, Maddaloni, Peydro, & Scopel, 2010). From BLS responses, Hempell & Sorensen (2010) analyze the propagation of the financial crisis, and especially the impact of the worsening, during the crisis, of banks' financing capacity, on the outstanding amounts of loans to households and enterprises. Applying a cross-country panel-econometric approach, they show that even when controlling for pure demand effects, supply-side constraints can affect loan growth. For France, as shown by Lacroix & Montornès (2009), the slowdown of business loans was caused by a tightening of credit standards and then by a fall in demand. The evolutions of credit to households were primarily explained by credit demand. Additionally, from the deep structure of the questionnaire, precise analyses of which factors have influenced the changes in credit standards and demand during the crisis have also been frequently presented.

Furthermore, there is a growing interest for individual banks responses to the Bank Lending Survey. Del Giovane, Nobili and Signoretti (2013), following Del Giovane, Eramo and Nobili (2011) estimate a structural econometric model to assess the impact of demand and supply factors on the cost and the dynamics of lending at the bank level. They provide additional evidence on the effects of the sovereign debt crisis on the credit market in Italy. Blaes (2011), using a panel approach based on a dataset matching individual responses to the BLS and micro data on loan quantities and prices, finds that credit supply and demand both contributed to the fall in bank lending in Germany during the crisis years.

In this study, the BLS balances of opinions are once more used as proxies of the credit supply and demand. However, the econometric model applied in this case, a disequilibrium model, differs from those of previous studies relying on the BLS. This methodology, in its static form, has already been applied to credit markets. Pazarbasioglu (1996) assessed the possible existence of a credit rationing in Finland due to the banking crisis of 1991. Similarly, the possibility of a credit crunch following the Asian crisis has been examined by E.G. Baek (2005). Finally, Hurlin & Kierzenkowski (2003) rely on this specification to model the loans growth rate in Poland. Generally, model inputs are quantitative macroeconomic variables such as interest rate spreads, GDP and indicators of healthiness of banks' balance sheets. Nevertheless, the choice of these variables may be controversial as they include information on both credit demand and supply.

Besides, following the last financial crisis, several publications focused on the financial constraints faced by European SMEs, at a micro and macro levels relying on quantitative as well as qualitative data. Ferrando & Mulier (2013) proposed a non parametric matching procedure to match individual responses to the SAFE survey with balance sheet information. Their goal is to evaluate the probability for a firm to be financially constrained according to its financial characteristics. Disequilibrium models have also been used for models at a micro level. For France, Kremp & Sevestre (2013), relying on a static "Tobit" disequilibrium model applied at the firms' level, show that the evolutions of credit flows to SMEs during the crisis were not caused by a credit rationing but more probably by a decreasing credit demand.

This study proposes an innovative approach, relying only on BLS balances of opinions considered as indicators of pure credit demand and supply. Besides, this approach, a dynamic disequilibrium model, differs from the previous studies; this methodology is more appropriate to circumvent the fact that BLS variables reflect the variations of credit demand and supply and not their levels. The model is applied on balances of opinions on credit standards and credit demand of French SMEs. As they rely heavily on the banking system for their financing, monitoring their access to credit markets has become a major challenge.

The model will be outlined within section 2 and the results will be presented in Section 3. Section 4 concludes.

II. Model description

1. A dynamic disequilibrium model

Since the 70s and the founding works of Fair & Kelejian (1974), disequilibrium models, as a limited dependent variable models, have become a broad research topic. As one of them, the cornerstone work of Maddala & Nelson (1974) proposing an estimation method for parameters based on the maximization of a full information likelihood function (FIML), raised much interest. At first, disequilibrium models, in their static form, were defined as models for which demand and supply are not observed simultaneously, only the minimum is, and both variables are approached by exogenous variables. Other models were then derived from the original ones, adding for instance an equation on prices, which permitted to identify the limiting variable between the supply and demand components. Nevertheless, estimation methods were not yet appropriate to estimate disequilibrium models with a dynamic component, allowing to take into account serial correlation or to introduce a lagged dependent variable in the demand or supply equation.

At the end of the 80s, Laroque & Salanié (1989; 1994) proposed a new estimation method for a static disequilibrium model in which parameters are estimated by minimizing a simulated pseudo maximum likelihood function of order 2 (SPML2). This estimation method showed comparable estimation and asymptotic properties as the FIML method. Besides, this method was found more flexible; instead of estimating explicitly the likelihood function, a simplified likelihood function is considered by assuming that, the observed variables, the minimum of the supply and demand, are well described by their two first moments. The two first moments are estimated by performing simulations of the supply and demand components. Besides, as opposed to the FIML approach, this estimation method may also be used to estimate a dynamic disequilibrium model. Laroque & Salanié (1993; 1996) have tested and then applied this estimation method to a dynamic disequilibrium model with a lagged dependent variable within the demand equation.

At the end of the 90s, other approaches to estimate a dynamic disequilibrium model were developed by Lee (1997) and Manrique & Shepard (1998). Lee proposed a simulation method, a recursive algorithm to estimate a likelihood simulator. Manrique & Shepard proposed an alternative method relying on Bayesian simulations. Other methods seem to outperform Laroque & Salanié (1993) in terms of the efficiency of the estimators. Nevertheless the Laroque & Salanié method is more flexible and easier to implement.

2. Specification of the model

In the present study, the estimation method proposed by Laroque & Salanié (1993) is considered to estimate a dynamic disequilibrium model with lagged dependent variables in both equations. The credit demand d_t and credit supply s_t equations are estimated from lagged BLS balances of opinions on credit demand BLS^D_{t-i} and credit supply BLS^S_{t-j}. Both variables are supposed to be strongly exogenous. Furthermore, the observed variable y_t, i.e. the net credit flows to SMEs, is defined as the minimum between the supply and demand components:

$$(1)\begin{cases} \boldsymbol{d_t = \alpha_1 + \gamma_1 d_{t-1} + \beta_1\, BLS^D_{t-i} + \varepsilon_{1,t}\, where\; \varepsilon_{1,t} \sim \mathcal{N}(0, \sigma_1^2)} \\ \boldsymbol{s_t = \alpha_2 + \gamma_2 s_{t-1} + \beta_2 BLS^S_{t-j} + \varepsilon_{2,t}\, where\; \varepsilon_{2,t} \sim \mathcal{N}(0, \sigma_2^2)} \\ \boldsymbol{y_t = \min(d_t, s_t)} \end{cases}$$

The residuals $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are assumed to be independently and normally distributed. An alternative model with a non-zero cross-correlation between the two residuals was also estimated; the correlation parameter was nevertheless not significant. The parameters $((\alpha_k)_{k\in\{1,2\}}, (\beta_k)_{k\in\{1,2\}}, (\gamma_k)_{k\in\{1,2\}}, (\sigma_k)_{k\in\{1,2\}})$ must be estimated.

From this dynamic model, a pseudo model can be derived; for which the observed variable yt is defined from its two first moments: its mean $\mathbb{E}[y_t|x_t]$ and its variance $\mathbb{V}[y_t|x_t]$):

$$(2)\quad \boldsymbol{y_t = \mathbb{E}[y_t|x_t] + \eta_t\; where\; \eta_t \sim \mathcal{N}(0, \mathbb{V}[y_t|x_t])}$$

These moments can be explicitly calculated for a static disequilibrium model but not for the present dynamic disequilibrium model. As a consequence, they must be estimated by performing simulations. For each time t in [1;T], H simulated trajectories[4] of demand and supply variables are estimated and, in this way, H simulated values of the observed variable yt. For this purpose, 2H*T values $(u^h_{i,t}, i \in \{1,2\}, h \in [\![1;H]\!], \mathrm{t} \in [\![1;\mathrm{T}]\!])$ are drawn from a standard normal distribution. These values, independently distributed according to t and h, are then used to simulate H values of the credit demand component d^h_t, the credit supply s^h_t, and the net credit flows y^h_t:

$$(3)\begin{cases} \boldsymbol{d^h_t = \alpha_1 + \gamma_1 d^h_{t-1} + \beta_1\, BLS^D_{t-i} + \sigma_1\, u^h_{1,t}} \\ \boldsymbol{s^h_t = \alpha_2 + \gamma_2 s^h_{t-1} + \beta_2 BLS^S_{t-j} + \sigma_2\, u^h_{2,t}} \\ \boldsymbol{y^h_t = \min(d^h_t, s^h_t)} \end{cases}$$

From these H values y^h_t, the first two simulated moments, the mean m^H_t and the variance v^H_t can be defined. In this case, as proposed by Laroque & Salanié (1993), moments chosen as inputs of the likelihood function (F^H_t, V^H_t) are moments of the

[4] The H parameter was set to 1200. Choosing fewer or more simulations has led to similar estimated values but this choice is an arbitrage between stability of results and convergence time.

instantaneous and lagged values of the simulated variable $Y_t^h = (y_t^h \ \ y_{t-1}^h)'$ to take into account the dynamic structure of the model:

$$(4) \ \boldsymbol{m_t^H} = \frac{\boldsymbol{1}}{\boldsymbol{H}}\sum_{\boldsymbol{h=1}}^{\boldsymbol{H}} \boldsymbol{y_t^h} \quad \boldsymbol{and} \ \boldsymbol{F_t^H} = (\boldsymbol{m_t^H} \ \boldsymbol{m_{t-1}^H})'$$

$$(5) \ \boldsymbol{V_t^H} = \frac{\boldsymbol{1}}{\boldsymbol{H-1}} \sum_{\boldsymbol{h=1}}^{\boldsymbol{H}} (\boldsymbol{Y_t^H} - \boldsymbol{F_t^H}) \ (\boldsymbol{Y_t^H} - \boldsymbol{F_t^H})^{\boldsymbol{T}}$$

The log-likelihood function l_T^H associated to the pseudo-model can be easily extracted from the previous equations. The likelihood function at time t l_t^H is defined as the probability density to observe y_t estimated from the pseudo-model. The log-likelihood function l_T^H, from which parameters are estimated by minimization, is then defined as the opposite of the sum of the logarithm of l_t^H:

$$(6) \ \boldsymbol{l_t^H} = \frac{\boldsymbol{1}}{\sqrt{\mathbf{det}\, \boldsymbol{V_t^H}}} \mathbf{exp}\left(-\frac{\boldsymbol{1}}{\boldsymbol{2}}[\boldsymbol{Y_t} - \boldsymbol{F_t^H}]^{\boldsymbol{T}} \boldsymbol{V_t^H}^{\boldsymbol{-1}} [\boldsymbol{Y_t} - \boldsymbol{F_t^H}]\right) \quad \boldsymbol{with}\, \boldsymbol{Y_t} = (\boldsymbol{y_t} \ \ \boldsymbol{y_{t-1}})'$$

$$(7) \ \boldsymbol{l_T^H} = -\sum_{\boldsymbol{t=1}}^{\boldsymbol{T}} \mathbf{log}(\boldsymbol{l_t^H})$$

The parameters were estimated by minimization of the log-likelihood function using a Levenberg-Marquardt algorithm.

Besides, the asymptotic distribution of the estimated parameters $\hat{\theta}$, where θ is defined as $\theta = ((\alpha_k)_{k \in \{1,2\}}, (\beta_k)_{k \in \{1,2\}}, (\gamma_k)_{k \in \{1,2\}}, (\sigma_k)_{k \in \{1,2\}})$ may be expressed as:

$$(8) \ \sqrt{\boldsymbol{T}}\left(\boldsymbol{\hat{\theta}} - \boldsymbol{\theta}\right) \underset{\boldsymbol{T \to \infty}}{\longrightarrow} \boldsymbol{\mathcal{N}}(\boldsymbol{0}, \boldsymbol{J_H}^{\boldsymbol{-1}} \boldsymbol{I_H} \boldsymbol{J_H}^{\boldsymbol{-1}})$$

Where J_H and I_H may be approached by:

$$(9) \ \widehat{\boldsymbol{J_H^T}} = \frac{\boldsymbol{1}}{\boldsymbol{T}} \sum_{\boldsymbol{t=1}}^{\boldsymbol{T}} \frac{\boldsymbol{\partial F_t(x^t, \hat{\theta})}}{\boldsymbol{\partial \theta}} \ \boldsymbol{V_t(x^t, \hat{\theta})^{-1}} \frac{\boldsymbol{\partial F_t(x^t, \hat{\theta})}}{\boldsymbol{\partial \theta'}} + \frac{\boldsymbol{1}}{\boldsymbol{2T}} \sum_{\boldsymbol{t=1}}^{\boldsymbol{T}} \boldsymbol{Tr}(\boldsymbol{V_t(x^t, \hat{\theta})^{-1}} \frac{\boldsymbol{\partial V_t(x^t, \hat{\theta})}}{\boldsymbol{\partial \theta}} \ \boldsymbol{V_t(x^t, \hat{\theta})^{-1}} \frac{\boldsymbol{\partial V_t(x^t, \hat{\theta})}}{\boldsymbol{\partial \theta'}})$$

Where the abbreviation Tr represents the trace function and xt the explanatory variables, i.e. the BLS balances of opinions.

And:

$$(10) \ \widehat{\boldsymbol{I_H^T}} = \frac{\boldsymbol{1}}{\boldsymbol{T}} \sum_{\boldsymbol{t=1}}^{\boldsymbol{T}} \frac{\boldsymbol{\partial l_t(\hat{\theta})}}{\boldsymbol{\partial \theta}} \frac{\boldsymbol{\partial l_t(\hat{\theta})}}{\boldsymbol{\partial \theta'}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{m_T}} \left(\boldsymbol{1} - \frac{\boldsymbol{i}}{\boldsymbol{m_T + 1}}\right) \frac{\boldsymbol{1}}{\boldsymbol{T}} \sum_{\boldsymbol{t=i+1}}^{\boldsymbol{T}} \frac{\boldsymbol{\partial l_t(\hat{\theta})}}{\boldsymbol{\partial \theta}} \frac{\boldsymbol{\partial l_{t-i}(\hat{\theta})}}{\boldsymbol{\partial \theta'}} + \frac{\boldsymbol{\partial l_{t-i}(\hat{\theta})}}{\boldsymbol{\partial \theta}} \frac{\boldsymbol{\partial l_t(\hat{\theta})}}{\boldsymbol{\partial \theta'}}$$

The matrices $\widehat{J_H^T}$ and $\widehat{I_H^T}$ are derived from first derivatives of the means (F_t), variances (V_t), and pseudo log-likelihood functions (l_t) obtained by first differences. The $\widehat{J_H^T}$ formula has been proposed by Gourieroux et. al. (1984), the $\widehat{I_H^T}$ by Newey & West (1987). The value m_T is determined endogenously as proposed by Andrews (1991).

3. Initialization of demand and supply trajectories

As both the demand and the supply equations contain a lagged dependent variable, a set of initial demand and supply observations $(d_0^h, s_0^h)_{h \in [\![1;H]\!]}$ is needed for the first iteration (time 1). For this purpose, some assumptions are made. The dataset considered begins at the second quarter of 2006, nevertheless, the observations of the second and third quarters of 2006 are kept to initialize the trajectories of supply and demand variables and are resumed into the notation (y_{-1}, y_0). Supply and demand are assumed to be at equilibrium and equal to the observed variable y_{-1} before the first observation date of the sample.[5] As both credit and demand equations are not strongly persistent, this hypothesis seems acceptable. Indeed, at time 0, the explained parts of supply and demand can be expressed by:

$$(11)\;\; \boldsymbol{d_{exp,0} = \alpha_1 + \gamma_1 y_{-1} + \beta_1 BLS^D_{-i}}$$

$$\boldsymbol{s_{exp,0} = \alpha_2 + \gamma_2 y_{-1} + \beta_2 BLS^S_{-j}}$$

From these expressions, the probability λ that the demand is the limiting state at 0 is:

$$(12)\;\; \boldsymbol{\lambda = \Phi\left(\frac{s_{exp,0} - d_{exp,0}}{\sqrt{\sigma_1^2 + \sigma_2^2}}\right)}$$

The notation ϕ accounts for the distribution function of the normal distribution.

To simulate H values (d_0^h, s_0^h), a vector of H random variables $(v_2^h)_{h \in [\![1;H]\!]}$ is drawn from a standard uniform distribution. For each h, if $v_2^h \leq \lambda$, demand is assumed to be the limiting state and equal to y_0, otherwise demand is assumed to be in excess and the demand value must be simulated. For this purpose, the unexplained part of demand is drawn from a normal distribution truncated at $\frac{y_0 - d_{exp,0}}{\sigma_1}$:

$$(13)\;\; \boldsymbol{For\ each\ h,}\quad \begin{cases} \boldsymbol{if\ v_2^h \leq \lambda\ then\ d_0^h = y_0} \\ \boldsymbol{else\ d_0^h = d_{exp,0} + \sigma_1 \varepsilon_{1,0}\ where\ \varepsilon_{1,0} = -\phi^{-1}\left(v_1^h \phi\left(-\frac{y_0 - d_{exp,0}}{\sigma_1}\right)\right)} \end{cases}$$

For each h, a random value v_1^h is drawn from a standard uniform distribution to simulate the truncated normal distribution.

Symmetrically, if $v_2^h > \lambda$, supply is assumed to be the limiting state and equal to y_0, otherwise supply is supposed to be in excess and must be simulated, by drawing the unexplained part of supply from a normal distribution truncated at $\frac{y_0 - s_{exp,0}}{\sigma_2}$:

$$(14)\;\; \boldsymbol{For\ each\ h,}\quad \begin{cases} \boldsymbol{if\ v_2^h > \lambda\ then\ s_0^h = y_0} \\ \boldsymbol{else\ s_0^h = s_{exp,0} + \sigma_2 \varepsilon_{2,0}\ where\ \varepsilon_{2,0} = -\phi^{-1}\left(v_1^h \phi\left(-\frac{y_0 - s_{exp,0}}{\sigma_2}\right)\right)} \end{cases}$$

[5] This initial choice does not seem aberrant; the balances of opinions on credit demand and credit supply prior to 2006 have been quite stable or reflecting a thriving economic environment.

From this methodology, H values of (d_0^h, s_0^h) are simulated. These simulations initialize each iteration step of the optimization algorithm, as some prior estimation of the parameters values is needed to simulate these values.

4. Choice of initial parameters

The choice of appropriate initial parameters is crucial considering that the likelihood function is not bounded, and may diverge if at least one standard deviation tends to 0 or if only one state, the supply or the demand, is the limiting state over the time period of the sample. The initial parameters have been set following the methodology proposed by Hurlin & Kierzenkowski (2003).

A first set of parameters $((\alpha_k^1)_{k\in\{1,2\}}, (\beta_k^1)_{k\in\{1,2\}}, (\gamma_k^1)_{k\in\{1,2\}}, (\sigma_k^1)_{k\in\{1,2\}})$ is estimated by considering the following equations:

$$(15)\quad \begin{aligned} \boldsymbol{y_t} &= \boldsymbol{\alpha_1^1 + \gamma_1^1 y_{t-1} + \beta_1^1\, BLS_{t-i}^D + \varepsilon_{1,t} = d_{exp,t}^1 + \varepsilon_{1,t}} \quad \boldsymbol{where\ \varepsilon_{1,t} \sim \mathcal{N}(0, \sigma_1^2)} \\ \boldsymbol{y_t} &= \boldsymbol{\alpha_2^1 + \gamma_2 y_{t-1} + \beta_2 BLS_{t-j}^S + \varepsilon_{2,t} = s_{exp,t}^1 + \varepsilon_{2,t}} \quad \boldsymbol{where\ \varepsilon_{2,t} \sim \mathcal{N}(0, \sigma_2^2)} \end{aligned}$$

From the results of the first estimation, the sample is divided into two subsamples. The first subsample is the demand one containing observations for time periods at which the demand side is more probably the limiting side (i.e. $d_{exp,t}^1 < s_{exp,t}^1$), and the second subsample contains the other ones (i.e. $d_{exp,t}^1 \geq s_{exp,t}^1$). The second set of parameters $((\alpha_k^2)_{k\in\{1,2\}}, (\beta_k^2)_{k\in\{1,2\}}, (\gamma_k^2)_{k\in\{1,2\}}, (\sigma_k^2)_{k\in\{1,2\}})$ is then estimated by regressing the variables yt from the first subsample on demand variables and those from the second subsample on supply variables. This set of parameters is then used to initialize parameters estimation.

5. Choice of lags for Bank Lending Survey variables

It is commonly assumed that evolutions of balances of opinions in the Bank Lending Survey precede those of quantitative data such as credit flows. Therefore, the balances of opinions must be delayed in the model equations. The lags i and j of BLS variables were initially determined by selecting, according to the AIC criterion, the best model of this form:

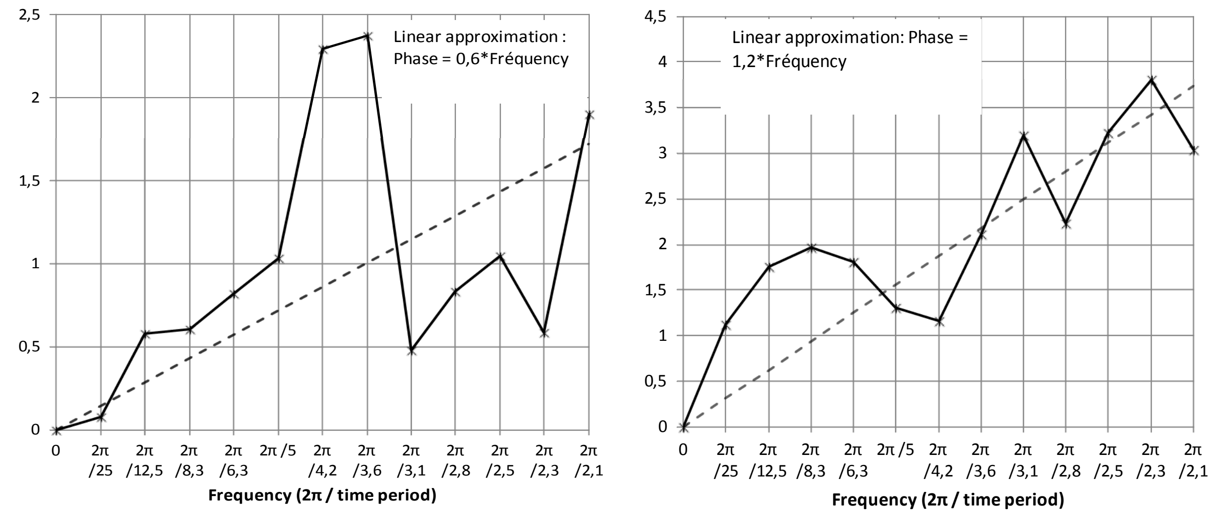
$$(16)\ \boldsymbol{y_t = \alpha\, y_{t-1} + \beta\, BLS_{t-i}^D + \gamma\, BLS_{t-j}^S + \varepsilon_t\ where\ \varepsilon_t \sim \mathcal{N}(0, \sigma^2)}$$

Where y_t represents net flows of credit and BLS_{t-i}^D and BLS_{t-j}^S account for balances of opinions on credit standards and demand respectively. The lags i and j can take any integer among {0,1,2,3}.

According to the AIC criterion, the best lags are 0 quarter for the demand component and 2 quarters for the supply component. This result is in line with the results obtained from an analysis in the frequency domain. From the Fourier transform of the cross-covariance between the net credit flows to SMEs and each BLS balance of opinions, the phase spectrum between the net credit flows to SMEs and each BLS balance of opinions can be extracted (Brocklebank & Dickey, 2003). The slope of phase spectrum corresponds to the time shift, in quarters, between the two variables. According to these results, the lag of the demand variable should be 0 or 1, and the lag of the supply variable should be 1 or 2.

Phase spectrum between BLS balances of opinions on credit demand to SMEs and net credit flows to SMEs (right figure) and phase spectrum between BLS balances of opinions on credit supply to SMEs and net credit flows to SMEs (left figure)

Figure 1



To meet both criteria, the AIC criterion and the frequency one, the selected lags are 0 for the demand component and 2 for the supply one.

III. Results

1. Dataset description

The approach favored in this study is a parsimonious model relying on few variables: the Bank Lending Survey balances of opinions and the net credit flows to SMEs. The two balances of opinions selected from the Bank Lending Survey represent banks' opinion on the quarterly variation of credit standards for SMEs and the quarterly variation of credit demand from SMEs. These balances of opinions are available from 2003 Q1 to 2014 Q1.The time series of net credit flows to SMEs is defined as the net variation of outstanding amounts of credits declared monthly by credit institutions and gathered into the Central Credit Register Database of the Banque de France. Data on outstanding drawn loans are reported by credit institutions on a monthly basis and at a firm level and then aggregated according to the category of their legal units. Only firms with a credit debt above 25 000 euros are reported.

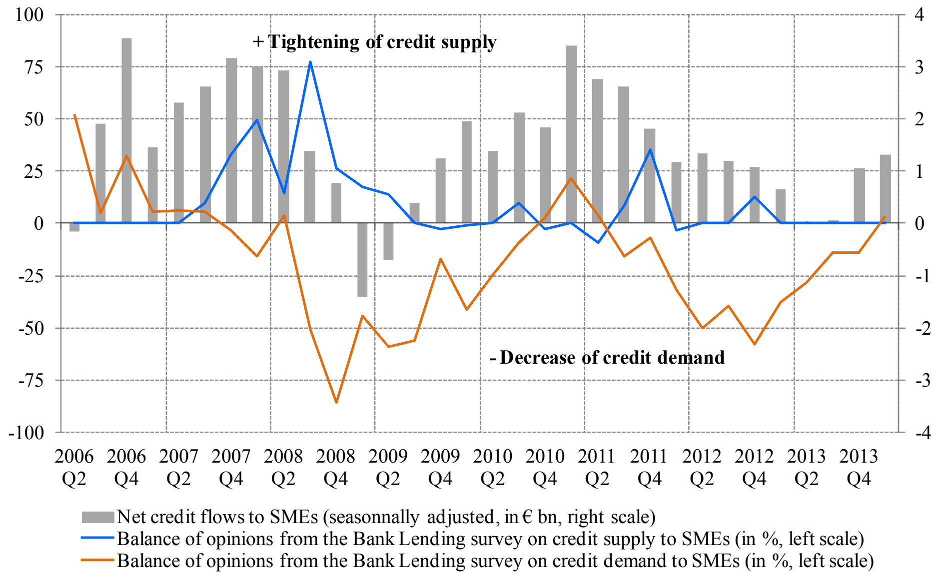
The definition of SME used in this paper is based on the usual combination of criteria: number of employees less than 250, annual turnover less than 50 million euros, and total balance sheet assets less than 43 million euros. It does not strictly stick to the new statistical definition of an enterprise published in the implementing regulation of the LME (French law for the Modernization of the Economy) and used by the Banque de France in its publications since 2013, because back data consistent with this definition are not yet available. The time series of credit flows is available on a quarterly basis from 2006 Q2 to 2014 Q1. The net credit flows have been seasonally adjusted with the procedure X12 of SAS Software; besides, responses given to the Bank Lending Survey do not present seasonality.

According to the BLS, credit standards to SMEs have remained stable from 2006 Q2 to 2007 Q3. During the financial crisis, credit standards have been strongly but transitorily tightened, due to balance sheet constraints faced by banks and the weakened economic environment. Since 2010, credit standards have been relatively stable with some punctual tightening peaks in 2011 Q4 and 2012 Q4. The evolutions of credit demand balances of opinions are close to those of macroeconomic variables such as GDP annual growth rate, or qualitative indicators such as evolution of cash flows positions of SMEs[6]. Credit demand has been quite stable or even improving until 2008 Q1, then credit demand kept falling until 2008 Q4. From 2008 Q4 to 2010 Q4, bankers continue to report a decreasing credit demand even though credit demand variations were less and less negative. The credit demand variations became punctually positive in 2011 Q1. From 2011 Q2 onwards, credit demand started to fall again, and recovered a positive level only in 2014 Q1. Over the period of estimation, the average balance of opinions on credit supply (resp. credit demand) to SMEs is positive (resp. negative), reflecting the overall deteriorated economic environment. Besides, the balances of opinions on credit demand are rather volatile compared to the credit supply ones.

The net credit flows to SMEs remain positive for almost all quarters, the outstanding amounts of credit to SMEs decreased only during the first semester of 2009. Nevertheless, net credit flows slowed down sharply from 2007 Q4 to 2009 Q1 and from 2011 Q1 to 2013 Q3.

Net flows of credit to SMEs (in € bn) and BLS balances of opinions related to SMEs credit supply and demand

Figure 2



6 The Banque de France business survey includes questions on cash flows positions of SMEs since 2003.

Average values and standard deviations of the variables over the period 2006 Q2–2014 Q1

Table 1

	Average value over the period 2006 Q2–2014 Q1	Standard deviation over the period 2006 Q2–2014 Q1
Net credit flows to SMEs, seasonally adjusted, in € bn	1.5	1.2
Balance of opinions from the BLS on credit supply to SMEs	9.0	18.0
Balance of opinions from the BLS on credit demand from SMEs	–17.5	29.7

As mentioned by Kierzenkowski & Hurlin (2003), the use of non-stationary time series as inputs of the models may lead to counter-intuitive results; the time series must be stationary (Laroque & Salanié, 1993). The stationarity of the time series has been tested with the ERS (Elliott, Rothenberg, and Stock) test, more appropriate for small samples. For all variables, the null hypothesis of non stationarity is rejected at a 10% threshold.

2. Results

This study falls within the same category as Kremp & Sevestre (2013), the search for the identification of the origin of SMEs' credit constraints. Besides, as opposed to them, the present approach is macroeconomic, which prevents a detailed analysis of the limiting constraints of the market but may help to bring into light easily available macroeconomic indicators of the credit market conditions.

Table 2 presents the estimated values of the parameters of the dynamic disequilibrium model previously specified. All parameters are significant at a 10% threshold and have the expected sign. The BLS parameter within the demand equation (resp. supply equation) has a positive sign (resp. negative sign) reflecting the increase of credit flows following an increase in demand (resp. an easing of credit standards). The BLS supply parameter exhibits a higher absolute value than the BLS demand parameter. Parameters associated with the lagged dependent variables are significantly lower than 1, which means that a transitory shock on both equations will be attenuated after a few quarters. Besides, the supply component is more persistent; indicating that the effects of a supply shock will last longer than those of a demand one.

As far as the magnitude of the effects is concerned, a demand shock at the quarter t, materialized by a fall in the demand balance of opinions of 10% on a specific quarter, is accompanied by a decrease of credit flows of 170 €m instantaneously and a cumulated loss over 5 quarters reaching 370 €m. A supply shock at quarter t of the same magnitude has larger effects: a rise in the supply balance of opinions of 10%, is followed by a decrease of 250 €m of credit flows after 2 quarters and a cumulated loss of 800 €m over 8 quarters.

Estimated values and standard deviations of the parameters		Table 2
Estimated coefficients and standard deviations	Demand equation	Supply equation
Constant value α	1.15	0.97
	(0.31)	(0.56)
BLS parameter β	0.017	–0.025
	(0.002)	(0.01)
Parameter of the lagged dependent variable γ	0.56	0.70
	(0.13)	(0.13)
Standard deviation of the residuals σ	0.46	0.91
	(0.12)	(0.45)

These first results do not reveal detailed information on the trajectories of the credit supply and demand components. For this purpose, average trajectories are estimated from the 1200 simulated trajectories used to estimate the parameters within the SPML2 algorithm. Considering the average of the initial distributions of supply and demand $(\hat{d}_0^m, \hat{s}_0^m)$, average trajectories may be estimated iteratively:

$$(17)\ \hat{\boldsymbol{d}}_t^m = \hat{\boldsymbol{\alpha}}_1 + \hat{\boldsymbol{\beta}}_1\, \boldsymbol{BLS}_t^D + \hat{\boldsymbol{\gamma}}_1 \hat{\boldsymbol{d}}_{t-1}^m$$

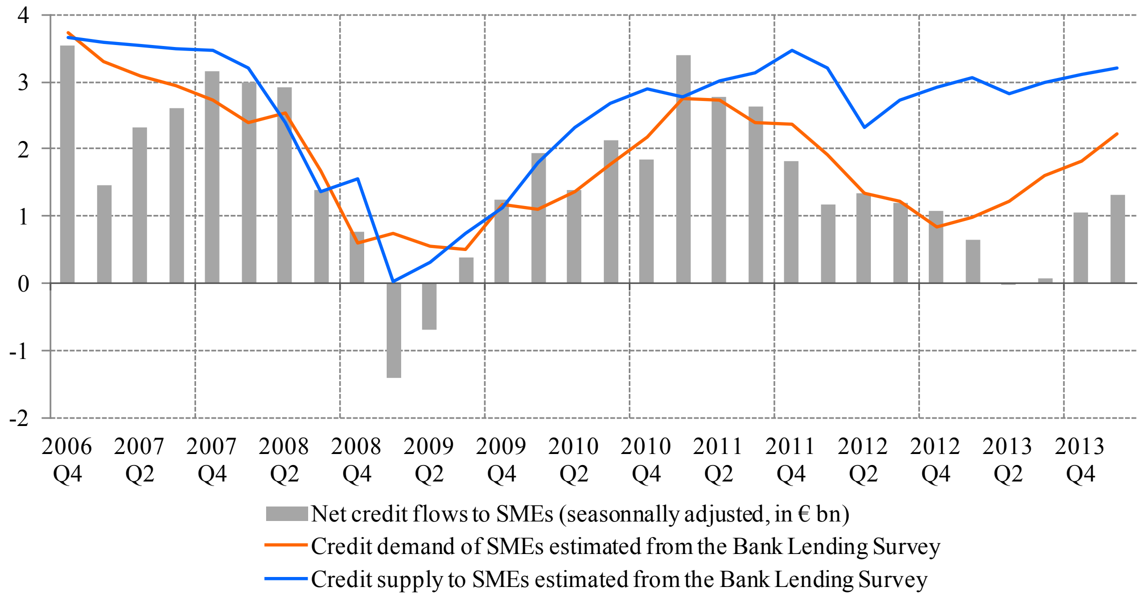
$$\hat{\boldsymbol{s}}_t^m = \hat{\boldsymbol{\alpha}}_2 + \hat{\boldsymbol{\beta}}_2\, \boldsymbol{BLS}_t^S + \hat{\boldsymbol{\gamma}}_2 \hat{\boldsymbol{s}}_{t-1}^m$$

The average trajectories of credit supply and demand from 2006 Q4 to 2014 Q1 are reported on the figure below. From these results, credit demand from SMEs has more probably limited credit flows between 2006 Q4 and 2008 Q1. Nevertheless, credit supply fell from 2008 Q1 to 2009 Q1. Following this sharp decline, supply has probably limited credit flows at least during the first semester of 2009. In 2010, both credit demand and supply have recovered their pre-crisis levels; however the demand started to fall again from the end of the first semester of 2011 to the end of 2012. Since 2013 Q1, credit demand has been increasing, but still seems to limit credit flows. These results are consistent with the findings of Kremp & Sevestre (2013) for France on micro data. All in all, supply constraints on credit to SMEs have materialized but on a very short and specific period in the aftermath of the financial crisis.

Besides, according to the model specification, the minimum between the credit demand and the credit supply estimated should be equal to the net credit flows. The trajectories of the minimum between the explained parts of credit demand and credit supply is nevertheless sometimes quite different from the net credit flows observed. This reflects the fact that residual errors (the unexplained part of both supply and demand equations) can be large for some periods. At this point, it should be noted that although our model allows for very rich dynamics, the "true" explanatory factors are reduced to a minimum. Besides, these factors (bankers' assessment on the current evolutions of credit flows) are by definition less precise than hard data. It thus appears that the ability of the model to fit the path of loans to SMEs over the period 2006–2013 is rather encouraging for further work.

Net credit flows to SMEs and average trajectories of credit supply and demand estimated

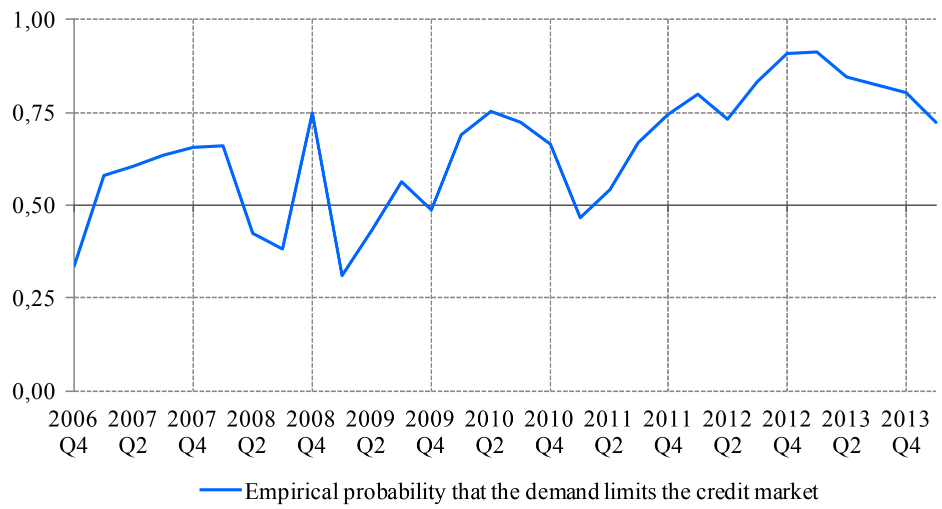
Figure 3



The probabilistic nature of the model may also be represented through the probability to be in one regime such as the credit demand regime. The empirical probability that the demand is the limiting regime is defined for each time as the ratio of credit demand simulated trajectories lower than credit supply simulated trajectories over the number of simulated trajectories. This representation also highlights periods for which the spread between credit demand and credit supply is significant. The period 2008–2009 is quite disrupted, making it hard to conclude on the existence of a credit rationing during this period.

Empirical probabilities that the credit demand limits the credit market

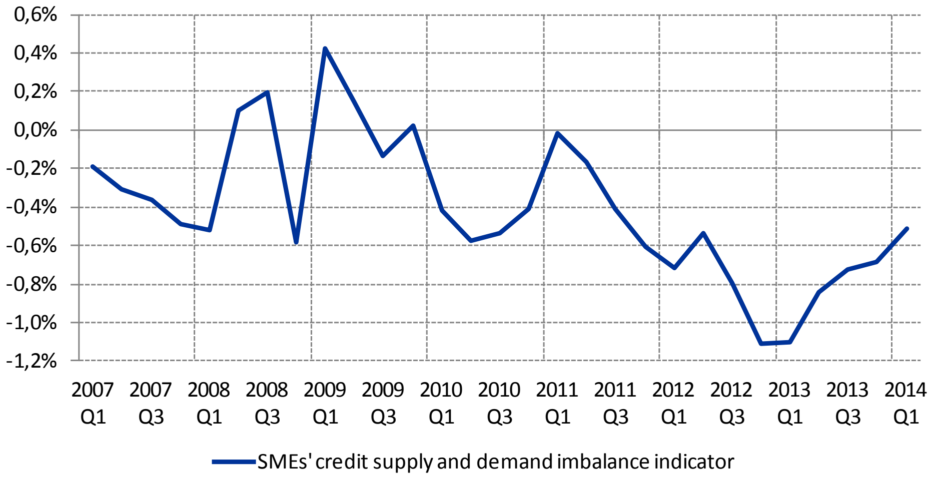
Figure 4



Finally the spread between the credit supply and credit demand trajectories can be interpreted as a loss relatively to a "balanced" credit distribution for which credit demand and credit supply are equal. Imbalances between SME's credit supply and demand can be measured by the distance between the average credit supply and credit demand trajectories, normalized by the outstanding amounts of credits at the previous quarter. According to this definition, the market is imbalanced by demand (resp. supply) when this rate is negative (resp. positive), and the imbalance is all the more important as the absolute rate value is higher. According to this indicator, the quarterly growth rate of credits to SMEs for 2014 Q1 could have been higher up to 0.5% if credit demand had been equal to credit supply.

SMEs credit supply and demand indicator

Figure 5



3. Conclusion and future work

Credit supply and credit demand from French SMEs have been estimated using a dynamic disequilibrium model. Simulated trajectories show that French SMEs have only been moderately and transitorily credit rationed in the aftermath of the financial crisis. Indeed, credit demand from SMEs seems to have sharply decreased during the Lehman Brothers crisis and during the sovereign debt crisis. These evolutions are in accordance with surveys conducted by the Banque de France (Guinouard, Kremp, & Randriamisaina, 2013). French SMEs do not currently encounter strong difficulties to be financed, but their credit demand is still sluggish.

Besides, this model is an innovative approach to interpret information embedded within BLS balances of opinions. From these results, new indicators, such as the probability to be in a credit demand limiting state or the loss due to the imbalance on the credit market, are proposed.

Furthermore, for the sake of simplicity, the model specification is quite parsimonious given the size of the sample. Nevertheless, as time goes by, this model could be enriched with other macroeconomic variables to reduce the unexplained part of the evolutions of credit flows, especially around turning points.

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