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A Micro Data Approach to the Identification of Credit Crunches *

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Abstract

This paper presents a micro data approach to the identification of credit crunches. Using a survey among German firms which regularly queries the firms' assessment of the current willingness of banks to extend credit we estimate the probability of a restrictive credit supply policy by time taking into account the creditworthiness of borrowers. Creditworthiness is approximated by firm–specific factors, e.g. the firms' assessment of their current business situation and their business expectations. After controlling for the banks' refinancing costs, which are also likely to affect the supply of loans, we derive a credit crunch indicator, which measures that part of the shift in the willingness to lend that is neither explained by firm-specific factors nor by refinancing costs.

JEL classifications: C23, E44, E51, G21

Key words: credit crunch, loan supply, surveys, nonlinear binary outcome panel–data models.

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1 Introduction

The world financial crisis that originated from the US subprime mortgage crisis of 2007 has shown a significant impact on the credit market in Germany. The annual growth rate of the outstanding amount of loans from German banks to non–financial corporations fell from more than 10 percent by the end of 2008 to –2.5 percent in November 2009. Since in Germany bank loans are a key source of external finance for firms, representing about 40 percent of nonfinancial corporations' debt, there was a lively discussion about whether the German economy is experiencing a credit crunch.

Following Udell (2009), "economists generally define a credit crunch as a significant contraction in the supply of credit reflected in a tightening of credit conditions." There is a large literature that has utilized macroeconomic data, such as the mix of bank loans and commercial paper, interest rate spreads, and total bank loans, to identify shifts in loan supply (Bernanke, 1983; Bernanke and Blinder, 1992; Kashyap and Stein, 1995; Kashyap, Stein, and Wilcox, 1993; Kashyap, Lamont, and Stein, 1994; Ding, Domac, and Ferri, 1998). However, approaches using aggregate data have been criticized for not having adequately isolated loan supply shocks from loan demand shocks. In fact, as Bernanke and Gertler (1995) and Oliner and Rudebusch (1996) argue, when the economy is hit by a negative shock, it is often impossible to distinguish whether the usual deceleration in bank lending stems from a shift in demand or supply. On the one hand, the corporate sector may be demanding less credit because fewer investments are undertaken; on the other hand, it could be that banks are less willing to lend and, therefore, charge higher interest rates or decline more credit applications.

In this paper we circumvent the identification problem of the macroeconomic approach by applying a micro data approach that uses information about the credit supply behavior of banks obtained from a regular survey among firms. In this survey firms are asked to give their perception of the current willingness of banks to extend credit to businesses. We interpret the responses to the credit question as information from the point of view of the firms about the banks credit supply conditions. Given this assumption our micro–econometric approach mimics the decision of a loan officer to grant credit to a firm by evaluating the creditworthiness of the firm subject to bank–specific restrictions. A major advantage of the survey is that it also provides ample information about the quality of each firm. The starting point of our analysis is Bernanke and Lown (1991) who also "define a bank credit crunch as a significant leftward shift in the supply curve for loans". They however emphasize that in any empirical approach the econometrician needs to hold "constant both the safe real interest rate and the quality of potential borrowers" in order to properly separate a credit crunch from 'normal' shifts in loan supply curve, which may be triggered by changes in the creditworthiness of borrowers or changes in the banks' refinancing costs.

The purpose of the paper is to derive a credit crunch indicator that represents shifts in the supply of loans, which can neither be explained by changes in the quality of potential borrowers, nor by variations in the refinancing costs of banks. In a first step we control for variations in the firms' quality over time and regress the responses to the credit question on the information about the creditworthiness of the firm using a nonlinear binary outcome panel–data model. In addition to the firm– and sector–specific information we also include a set of time dummies as regressors into our model. The estimated coefficients on the time dummies are interpreted as additional macroeconomic or bank industry–specific factors determining the decision of the loan officer. In a second step we separate the variation of lending policies, which is captured by the time dummy coefficients, from changes in the banks' refinancing costs. This is achieved by regressing the estimated time dummy coefficients on the evolution of the refinancing costs over time using a simple linear regression model. The variation of the time dummy coefficients, which cannot be explained by changes in the refinancing cost, i.e. the residuals of the linear regression, are finally interpreted as bank industry–specific determinants of credit supply. The more positive the contribution of the bank industry–specific determinants of credit supply to the firms' perception of a restrictive willingness to lend (holding constant both the refinancing costs of banks and the quality of potential borrowers), the higher the probability that the economy is affected by a credit crunch.

Our results show that the probability of a credit crunch in the German economy was high in the years 2003 to 2005, following the economic downturn after the burst of the New Economy Bubble. In the subsequent boom of the years 2006 to 2008 the credit supply of banks was very lax. Even after controlling for the on average good quality of the firms and the low level of refinancing costs, the banks' willingness to lend was perceived as accommodating. Most surprisingly, in the latest financial crisis, in which banks are much more involved than in previous recessions due to massive write–downs of toxic assets, the indications of a credit crunch are rather weak. Only large firms that mainly negotiate credits with state–owned landes banks and private commercial reported a subdued willingness of the banks to grant credit, which can neither be explained by the impaired creditworthiness of these firms, nor by the large increase of the banks' financing premia on the capital markets.

To our knowledge this paper is the first to identify credit crunches by using direct (qualitative) information about credit supply conditions that is obtained from a survey among firms. To some extent our paper is close to the paper by Borensztein and Lee (2002) who analyzed the Korean credit market situation in the aftermath of the Asian financial crisis in 1997/1998 by using firm–level data. They pointed out that "one of the crucial issues related to the credit crunch is the extent to which profitable and viable firms did or did not have access to finance." They tried to tackle this problem by looking at the characteristics of firms that observed reductions in their bank credit volumes. However, since their dependent variable was credit volume, the identification problem still remained and credit supply shifts had to be identified by including some proxies for credit demand into the regression. Another strand of the literature used bank–level data in order to identify a credit crunch, which is typically caused by banks encountering difficulties on the liability side of their balance sheet and, in particular, in maintaining an adequate level of equity (Peek and Rosengren, 1995; Peek and Rosengren, 2000; Woo, 2003). A major shortcoming of this approach is, however, that changes in the quality of firms are not controlled for. Since differences in bank capital are likely to be associated with differences in borrowers quality, differences in credit growth may just reflect differences in firms' conditions rather than in banks' conditions. A rather new literature therefore proposes to analyze individual loan data together with both, firm and bank characteristics. Albertazzi and Marchetti (2010) use data on outstanding loans extended by Italian banks to Italian firms, merged with data on corresponding balance sheet indicators of the firms' quality. Since the compilation of a micro–data set with bank–firm relationships is a challenging task, Albertazzi and Marchetti (2010) are not able to analyze the evolution of loan supply over time and only provide a cross–sectional analysis for a specific point in time after the collapse of Lehman Brothers.

This paper is structured as follows. Section 2 presents the first step of our approach, the micro–econometric model. In Section 3 the credit crunch indicator is derived in the second step. Section 4 discusses the of role firm size and of bank lending relationships for our results. Section 5 concludes.

2 The Micro–Econometric Model

We consider the following nonlinear panel–data model for the binary choice variable y_{it},

$$Pr(y_{it} = 1|x_{it}, \beta, \alpha_i) = F(\beta' x_{it} + \alpha_i), \tag{1}$$

where x_{it} are the regressors, $i = 1, 2, \ldots, N$ denotes the independent firms and $t = 1, 2, \ldots, T_i$ denotes the observations for the ith unit. F is the cumulative logistic distribution function. In the pooled model it is assumed that $\alpha_i = \alpha$. A random effects (_re) model treats the individual–specific effect α_i as an unobserved random variable with a specified distribution, typically the normal distribution. In a fixed effects (_fe) model the α_i are also treated as unobserved random variables, which however may be correlated with the regressors x_{it}. In short panels the joint estimation of the N fixed effects and the other model parameters β usually leads to inconsistent estimation of all parameters due to the incidental parameters problem. One method of consistent estimation is the conditional maximum likelihood estimator, which is based on a log density for the ith individual that conditions on the total number of outcomes equal to 1 for a given individual over time. This leads to the loss of those observations where $y_{it} = 0$ or $y_{it} = 1$ for all t. If we ignore the firms without any within–group variation, the sample size decreases from 56946 to 44041 observations.

The big loss of degrees of freedom that is associated with the fixed effects model can be avoided if the individual effects are assumed to be random. In contrast to the random effects model, the fixed effects model makes inference based only on the intra–firm variation of the variables. But the random effects model hinges on the unlikely assumption, that the α_i are independent from all x_i. To overcome this limitation we use an approach suggested by Mundlak (1978) and Chamberlain (1980, 1984) and allow for correlation between α_i and x_i. The random effects are expressed as a linear function of the regressors[1]

$$\alpha_i = \gamma' \bar{x_i} + \eta_i, \tag{2}$$

where $\bar{x_i}$ denotes the firm–specific time averages of the regressors x_{it}, and η_i is a normally distributed error term. In a linear model it is not restrictive to decompose α_i according to equation (2). But in a nonlinear model, we must assume that the regression function $E(\alpha_i|\bar{x_i})$ is actually a linear function, and η_i is independent from x_i (Hsiao, 2003, Ch. 7). The probability in the case of the correlated random effects (_re_cham) model can now computed as

$$Pr(y_{it} = 1|x_{it}, \bar{x_i}, \beta, \gamma, \eta_i) = F(\beta' x_{it} + \gamma' \bar{x_i} + \eta_i). \tag{3}$$

2.1 Data

In all regressions the dependent variable y_{it} is *credit*, which measures the firms' perception of the banks' credit conditions. It is taken from the Ifo Business Survey, in which a representative sample of German firms of the manufacturing sector are asked to respond to the following question: "How would you assess the current willingness of banks to extend credit to businesses"? The answers to choose from are "accommodating", "normal" and "restrictive". The dependent variable is set equal to 1, if the firms assess the banks' credit supply policy as "restrictive", and 0 if the firms indicate "normal" or "accommodating". The question was introduced in the questionnaire in June 2003 and since then asked every March and August. In order to gain more information on the effects of the latest financial crisis on the financing situation of firms, the credit question was

[1] Instead of the firm–specific time averages $\bar{x_i}$, Chamberlain used x_i, the vector of all explanatory variables across all time periods. Our specification (Mundlak's version) conserves on parameters.

included in the regular monthly survey from November 2008 on. The November 2009 survey is the latest survey that is included in the sample. On average we have 2300 responses to the credit question in each survey.

The regressors x_{it} consist of two groups of variables. The first group comprises the firm–specific and sector–specific variables, which measure the quality of the potential borrowers. The firm–specific variables vary both, over time and across firms, and are also taken from the Ifo Business Survey. In our regressions we use the firms' assessments of the current state of the business (*statebus*) and their business expectations for the next six months (*comexp*) as a proxy for the quality of the borrower. The survey respondents can characterize their state of the business as "good", "satisfactory" or "poor" and their expectations as "more favorable", "unchanged" or "more unfavorable". Thus, both firm–specific regressors are ordinal variables with three categories, which take a value of

– 1, if the firm's quality is good (more favorable business expectations, good state of the business),
– 2, if the firm's quality is moderate (unchanged business expectations, satisfactory state of the business),
– 3, if the firm's quality is bad (more unfavorable business expectations, poor state of the business).

Of course other measures, in particular balance sheet ratios, could also be taken into account as proxies for the information used by the banks in order to evaluate the quality of potential borrowers. As such ratios are currently not yet available in the data set, we motivate our choice of the explanatory variables by the existing evidence from internal surveys, according to which the responses to these questions can be viewed as proxies for actual balance sheet figures. In the so–called "survey of the survey" the Ifo Institute examined the factors that form the basis for firms' replies to the monthly business survey. It turned out that for the assessment of the current state of the business and the business expectations for the next six months the firms mainly rely on hard facts, such as the profit situation and the turnover (Abberger, Birnbrich, and Seiler, 2009).

In addition to firm–specific variables we also include a sector–specific variable, *sectorclimate*. The idea here is that a firm's creditworthiness is also evaluated on the basis of the performance of the economic activity in the business sector that a firm i is operating in. This variable varies over time, but is identical for all firms producing in a specific business sector. The business sectors in manufacturing are defined according to the Classification of Economic Activities in the European Community (NACE rev. 1.1). As a proxy for the sector–specific economic activity, we use the Sector Ifo Business Climate Indicator, which is calculated as the geometric mean of the aggregated balances of the current business situation and the business expectations in a specific business sector. The balance values are calculated as the difference of the percentages of the positive and the negative responses. Table 1 shows that there is considerable variation of the mean of the Business Climate Indicator across sectors. While for example in the chemical sector (DG), which accounts for about 6 percent of the observations, firms report on average much more favorable business situations and expectations, the economic activity in the textile sector (DB with about 5 percent of the observations) is more depressed on average.

Table 1: Sector–specific Economic Activity

climatesector	mean	sd	N
DA (food products, beverages and tobacco)	-6.33	7.14	3313
DB (textiles and textile products)	-22.64	15.25	2714
DC (leather and leather products)	-22.49	16.77	683
DD (wood and wood products)	-17.29	14.56	2209
DE (pulp, paper and paper products; publishing and printing)	-15.22	16.84	8303
DF (coke, refined petroleum products and nuclear fuel)	-5.46	34.72	176
DG (chemicals, chemical products and man–made fibres)	3.16	22.74	3693
DH (rubber and plastic products)	-13.44	21.30	3623
DI (other non–metallic mineral products)	-18.95	17.45	3222
DJ (basic metals and fabricated metal products)	-17.15	25.98	8368
DK (machinery and equipment n.e.c.)	-11.89	27.28	9248
DL (electrical and optical equipment)	-12.49	26.28	6818
DM (transport equipment)	-24.69	32.09	1864
DN (not elsewhere classified)	-19.67	17.73	2712
Total	-14.04	23.21	56946

The descriptive statistics for the variables are shown in Table 2. The sample comprises 56946 responses to the credit question over the period 2003 to 2009. In 39 percent of the cases the firms assessed the banks' credit supply policy as "restrictive". On average, those firms are characterized by a poorer state of the business (i.e. a higher value of *statebus*), more unfavorable business expectations (i.e. a higher value of *comexp*) and a lower business activity in the sector they are operating in (i.e. a lower *climatesector*).

Table 2: Descriptive Statistics

credit	variable	mean	sd	min	max	N
1 (restrictive)	*statebus*	2.38	0.65	1	3	21945
	comexp	2.16	0.68	1	3	21945
	climatesector	-18.85	20.65	-70.6	53.6	21945
0 (else)	*statebus*	2.04	0.7	1	3	35001
	comexp	2.05	0.63	1	3	35001
	climatesector	-11.02	24.19	-70.6	53.6	35001
Total	*statebus*	2.17	0.7	1	3	56946
	comexp	2.1	0.65	1	3	56946
	climatesector	-14.04	23.21	-70.6	53.6	56946

Notes: *credit* = 1, if the firms assess the banks' credit supply policy as "restrictive", *credit* = 0, if the firms indicate "normal" or "accommodating".

The second group of regressors are thought to capture all variation of lending policies over the business cycle, which is independent from the quality assessment of the loan officer. We include a set of $T-1$ time dummies, where $T = 25$ is the number of surveys between June 2003 and November 2009 that are analyzed in the regressions. In contrast to the firm–specific or sector–specific variables the time dummies are common to all firms. The estimated coefficients on the time dummies are interpreted as additional macroeconomic or bank industry–specific factors determining the decision of the loan officer.

2.2 Regression Results

The results of the logit regressions are shown in Table 3. The coefficients on the quality measures are significant and have the correct sign. If the state of the business is "bad" or business expectations are "more unfavorable", the probability that a firm perceives the credit supply policy of banks as restrictive increases. If the economic activity in the sector that a firm belongs to increases, the probability of a restrictive credit supply policy decreases. These results are robust across the assumption made with respect to α_i (column (1) shows the results of the pooled model, column (2) those of the random effects model, column (3) those of the correlated random effects model, column (4) those of the fixed effects model, and column (5) those of the correlated random effects model with a sample identical to fixed effects model) and the distribution function F (the results of the linear model are shown in Table 7 in Appendix A; the results of the probit model are available from the authors upon request).

The coefficients on the time dummies (indicated as t_yymm, where yy stands for the year and mm for the month of the survey) are significantly different from zero (except for the year 2004) and show a pronounced cyclical behavior. Starting at their maximum level in 2003, the estimated coefficients continuously fall and reach their minimum in August 2007. From then on, they start to increase again until the end of the sample in November 2009. This U–shaped pattern implies that for a given quality of a firm, as measured by the firm and sector–specific variables, the firm's access to credit was less restrictive in 2007 than in 2003 or 2009 (see Figure 1). Interestingly, the coefficients on the time dummies are unaffected by the way how the firm–specific effects are modeled, except for the case when the individual effects are ignored (pooled logit).

In general, the estimated parameters β from the binary regression model (which include the coefficients on the time dummies) provide information about the sign and the statistical significance of the relationship between an independent variable and the outcome. More substantively meaningful interpretations are based on the predictive probabilities

$$\widehat{Pr}(y_{it} = 1 | x^*, \widehat{\beta}, \widehat{\alpha_i}) = F(\widehat{\beta}' x^* + \widehat{\alpha_i}), \tag{4}$$

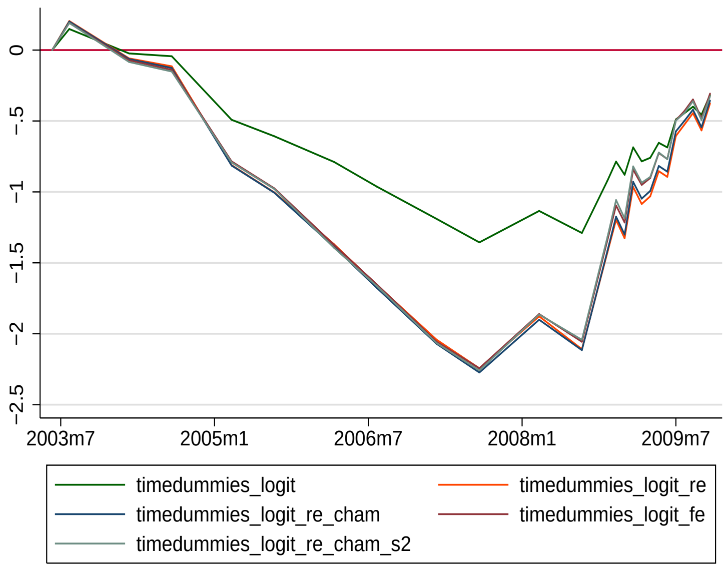
which are calculated for given values of the regressors x^*. While the calculation of the predicted probabilities in the case of a pooled logit model is straightforward, predictions in the case of the fixed or the random effects model can only be computed under the assumption that $\alpha_i = 0$ for all i. In the conditional fixed effects logit model no coefficients for time–invariant variables can be estimated. The time–invariant fixed effects are eliminated by conditioning on x_{it} and the sum of possible outcomes for y_{it}. In this procedure the constant term becomes essentially part of the fixed effects and is therefore also eliminated. Since the

Table 3: Results of the Logit Model

	(1)	(2)	(3)	(4)	(5)
	logit	logit_re	logit_re_cham	logit_fe	logit_re_cham_s2
statebus	0.566***	0.559***	0.470***	0.460***	0.467***
	(19.85)	(23.48)	(19.13)	(18.63)	(19.13)
comexp	0.124***	0.137***	0.124***	0.123***	0.122***
	(4.84)	(6.07)	(5.37)	(5.30)	(5.28)
climatesector	-0.007***	-0.013***	-0.013***	-0.011***	-0.010***
	(-4.43)	(-9.29)	(-9.21)	(-7.84)	(-7.64)
t_0308	0.149***	0.205**	0.201*	0.192*	0.191*
	(3.54)	(2.62)	(2.57)	(2.40)	(2.33)
t_0403	-0.024	-0.059	-0.063	-0.072	-0.084
	(-0.45)	(-0.74)	(-0.80)	(-0.89)	(-1.02)
t_0408	-0.044	-0.115	-0.127	-0.140	-0.151
	(-0.77)	(-1.39)	(-1.53)	(-1.66)	(-1.78)
t_0503	-0.491***	-0.811***	-0.814***	-0.785***	-0.792***
	(-8.94)	(-10.06)	(-10.09)	(-9.59)	(-9.62)
t_0508	-0.608***	-1.004***	-1.006***	-0.975***	-0.979***
	(-10.57)	(-12.06)	(-12.07)	(-11.56)	(-11.57)
t_0603	-0.789***	-1.369***	-1.388***	-1.374***	-1.394***
	(-9.98)	(-14.36)	(-14.54)	(-14.09)	(-14.47)
t_0608	-0.963***	-1.656***	-1.677***	-1.652***	-1.664***
	(-11.93)	(-16.76)	(-16.96)	(-16.38)	(-16.68)
t_0703	-1.190***	-2.042***	-2.071***	-2.057***	-2.066***
	(-12.83)	(-18.94)	(-19.19)	(-18.59)	(-19.00)
t_0708	-1.356***	-2.244***	-2.273***	-2.243***	-2.259***
	(-14.88)	(-20.39)	(-20.65)	(-19.88)	(-20.28)
t_0803	-1.134***	-1.877***	-1.901***	-1.861***	-1.864***
	(-14.09)	(-18.65)	(-18.88)	(-18.18)	(-18.45)
t_0808	-1.289***	-2.109***	-2.115***	-2.056***	-2.043***
	(-20.11)	(-23.23)	(-23.31)	(-22.36)	(-22.27)
t_0811	-0.919***	-1.424***	-1.413***	-1.338***	-1.316***
	(-14.70)	(-16.67)	(-16.53)	(-15.42)	(-15.29)
t_0812	-0.786***	-1.198***	-1.174***	-1.095***	-1.057***
	(-11.24)	(-13.09)	(-12.83)	(-11.77)	(-11.51)
t_0901	-0.879***	-1.327***	-1.301***	-1.215***	-1.187***
	(-13.20)	(-15.26)	(-14.95)	(-13.74)	(-13.57)
t_0902	-0.686***	-0.965***	-0.929***	-0.843***	-0.820***
	(-9.90)	(-10.98)	(-10.56)	(-9.39)	(-9.27)
t_0903	-0.785***	-1.085***	-1.047***	-0.950***	-0.935***
	(-11.57)	(-12.44)	(-11.99)	(-10.64)	(-10.61)
t_0904	-0.759***	-1.031***	-0.993***	-0.902***	-0.895***
	(-11.52)	(-11.97)	(-11.52)	(-10.25)	(-10.29)
t_0905	-0.654***	-0.854***	-0.817***	-0.726***	-0.722***
	(-10.04)	(-9.97)	(-9.53)	(-8.28)	(-8.33)
t_0906	-0.686***	-0.894***	-0.857***	-0.768***	-0.769***
	(-11.01)	(-10.66)	(-10.21)	(-8.97)	(-9.06)
t_0907	-0.489***	-0.606***	-0.573***	-0.495***	-0.497***
	(-8.40)	(-7.39)	(-6.98)	(-5.90)	(-5.97)
t_0908	-0.445***	-0.525***	-0.499***	-0.430***	-0.443***
	(-7.78)	(-6.41)	(-6.09)	(-5.14)	(-5.32)
t_0909	-0.399***	-0.445***	-0.421***	-0.348***	-0.361***
	(-6.48)	(-5.13)	(-4.85)	(-3.92)	(-4.09)
t_0910	-0.456***	-0.566***	-0.544***	-0.482***	-0.493***
	(-7.99)	(-6.99)	(-6.72)	(-5.83)	(-5.98)
t_0911	-0.317***	-0.376***	-0.356***	-0.307***	-0.326***
	(-5.44)	(-4.58)	(-4.34)	(-3.64)	(-3.89)
statebus_m			1.166***		0.221**
			(12.84)		(2.87)
comexp_m			0.026		-0.072
			(0.24)		(-0.79)
_cons	-1.497***	-1.544***	-3.925***		-1.300***
	(-16.93)	(-16.42)	(-15.75)		(-6.14)
lnsig2u					
_cons		1.662***	1.638***		0.648***
		(47.82)	(47.02)		(17.80)
N	56946	56946	56946	44041	44041
AIC	70429.91	52760.41	52577.71	32677.40	47147.43
LogL	-3.5e+04	-2.6e+04	-2.6e+04	-1.6e+04	-2.4e+04

t statistics, which are shown in parentheses, are clustering on individual firms in the case of the pooled model (1).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Coefficients on Time Dummies



fixed effects are not estimated, it is not possible to compute predicted probabilities or marginal effects with the estimated coefficients. In the case of the random effects model the calculation of predicted probabilities depends on the density function of the estimated random effects (Cameron and Trivedi, 2009). If predicted probabilities are calculated under the assumption that $\alpha_i = 0$ for all i, the result may be different from the unconditional probability, which should take account of the estimated distribution of α_i. Thus, any calculation of predicted probabilities in a random or fixed effects model requires an assumption on the distribution of the unobserved α_i, which may lead to a significant bias in the predictions.

Another problem that is related to the calculation of predicted probabilities is the choice of x^*. If for example we were interested in the probability of a restrictive credit supply for a creditworthy firm, we should be able to identify values for the explanatory variables that are compatible with a good quality of the potential borrower. While such a decision would be rather uncontroversial with respect to the ordinal variables *statebus* and *comexp*, there is no "natural" reference value for a continuous variable like *climatesector*. Finally, also in a non–linear model it holds that that the probability of a restrictive credit supply is larger at a given point in time, the greater the coefficient of the respective time dummies is. For these reasons we decided to not calculate predictions in the case of the non–linear model and to focus the subsequent analysis on the estimated coefficients of the time dummies.

A more meaningful interpretation of the estimated coefficients can however be given in the context of a linear probability model:

$$Pr(y_{it} = 1|x_{it}, \beta, \alpha_i) = \beta' x_{it} + \alpha_i. \quad (5)$$

In this class of models the estimated coefficients on the time dummies are percentage points contributions to the probability that a firm perceives the current willingness of banks to extend credit to businesses as restrictive, everything else being equal. It is well known that the disadvantage of the linear probability model is that the fitted probabilities may fall outside of the zero–one interval, which, however, does not apply in our case.[2] Table 7 in Appendix A shows that for a given firm the probability of a restrictive credit supply was, depending on the assumption made with respect to α_i, between 27 and 30 percentage points lower in August 2008 than in August 2003.

Another advantage of the the linear probability model is that we can easily implement instrumental variable regressions in order to account for the potential endogeneity of the regressors. If a firm faces a restrictive credit supply, profitable investments cannot be financed. Thus, it is possible that the firms assessment about the banks' credit supply policy *credit* may have an impact on the quality of the firm as measured by the regressors *statebus* and *comexp*. Whether or not this leads to the problem of endogenous regressors, crucially depends on the time horizon of the survey respondents. On the one hand, today's access to credit is likely to affect investment projects only in the future. On the other hand, the responses to the question about the current state of the business and the short–run business expectations may already incorporate these long–run effects of today's credit supply conditions. If our firm–specific regressors were endogenous, the pooled OLS and the fixed effects estimators would be biased

[2]These results are available from the authors upon request.

and there would only be little trust in the estimates of the probability models. In order to account for the potential endogeneity of the regressors *statebus* and *comexp*, we estimate both the pooled and the fixed effects linear probability model with IV methods (see the last two columns (5) and (6) in Table 7 in Appendix A). Various tests summarized in Appendix B show that there is no evidence of weak or endogenous instruments. Furthermore, we cannot reject the null hypothesis that *statebus* and *comexp* are exogenous. Based on these results we assume that also our baseline logit regressions are not subject to endogeneity problems. Finally, all the conclusions drawn henceforth based on the logit models are almost identical to the results of the linear IV models.

3 Credit Crunch Indicator

In the second step we separate the variation of lending policies over the business cycle, which is captured by the time dummy coefficients, from changes in the determinants of credit supply, which are caused by factors other than the firm–specific quality. From the credit crunch definition of Bernanke and Lown (1991) follows that a shift in the credit supply of banks can also be explained by changes in the banks' refinancing costs. If refinancing costs increase, banks will reduce their credit supply, implying that new loans are provided at a higher interest rate, everything else being equal.

Under the assumption that the costs of credit are taken into account by the survey respondents when assessing the banks' lending policies, we isolate the shifts in credit supply that reflect a credit crunch by regressing the estimated time dummy coefficients on the evolution of the refinancing costs over time using a simple linear regression model:

$$\widehat{td_t} = c + \delta' i_t + \varepsilon_t. \tag{6}$$

$\widehat{td_t}$ corresponds to the estimated coefficients on the time dummies t_yymm shown in Table 3, c is the intercept, and i_t is an interest rate spread, which is defined as the average government bond rate (average yield on all public debt securities outstanding) over the three–month treasury bills rate.[3] The variation of the time

[3]In Germany, bank debt securities are an important source of financing credit business.

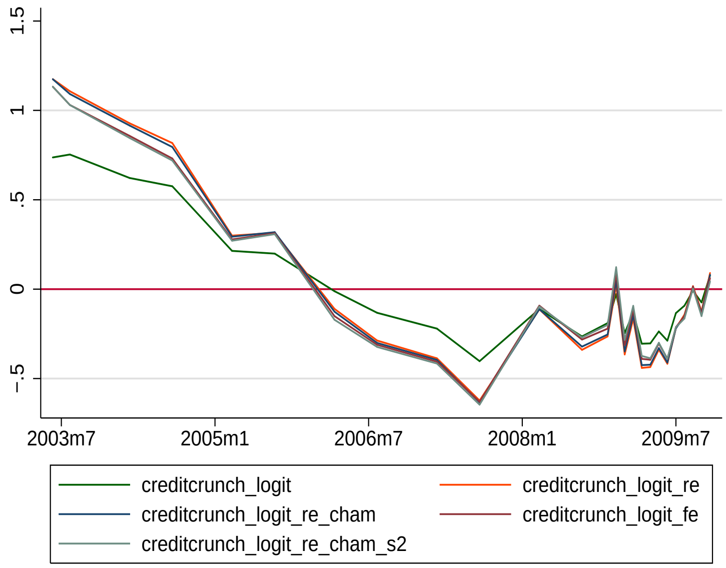
dummy coefficients, which cannot be explained by changes in the refinancing cost, i.e. the residuals ε_t of the linear regression, are finally interpreted as bank industry–specific determinants of credit supply. The more positive the contribution of the bank industry–specific determinants of credit supply to the firms' perception of a restrictive willingness to lend (holding constant both the refinancing costs of banks and the quality of potential borrowers), the higher the probability that the economy is affected by a credit crunch.

The estimated coefficients on the interest rate spread δ are positive and significant, implying that higher refinancing costs may contribute to a leftward shift of the credit supply curve. The residuals of the regression, which we denote as credit crunch indicator, are depicted in Figure 2. Irrespective of the specification of the panel–data model, our results show that the probability of a credit crunch in the German economy was high in the years 2003 to 2005, following the economic downturn after the burst of the New Economy Bubble. In the subsequent boom of the years 2006 to 2008 the credit supply of banks was very lax. Even after controlling for the on average good quality of the firms and the low level of refinancing costs, the banks' willingness to lend was perceived as accommodating. Most surprisingly, in the latest financial crisis, in which banks are much more involved than in previous recessions due to massive write–downs of toxic assets, the indications of a credit crunch are rather weak.

Since a straightforward interpretation of the estimated coefficients of a non–linear probability model is difficult, we also consider the results of the linear model. Figure 3, which compares the credit crunch indicator resulting from a correlated random effects linear model (depicted on the left axis) with the

With about 22% of the banks' liabilities, debt securities issued are one of the largest items in the banks' aggregate balance sheet, after deposits with about 43% and liabilities against other banks with about 32%. Instead of using the average yield on all bank debt securities outstanding for calculating the interest rate spread, we took the risk–free government bond rate, so that the interest rate spread actually reflects a term spread. The reason for this is simply the fact that during the financial crisis banks had to pay a risk premium over government bond rates (reaching 90 basis points in December 2008), which per se indicates that banks were in trouble. And it is exactly this type of trouble, which could lead to a credit crunch and, hence, should not be taken into account when calculating the credit crunch indicator.

Figure 2: Credit Crunch Indicator

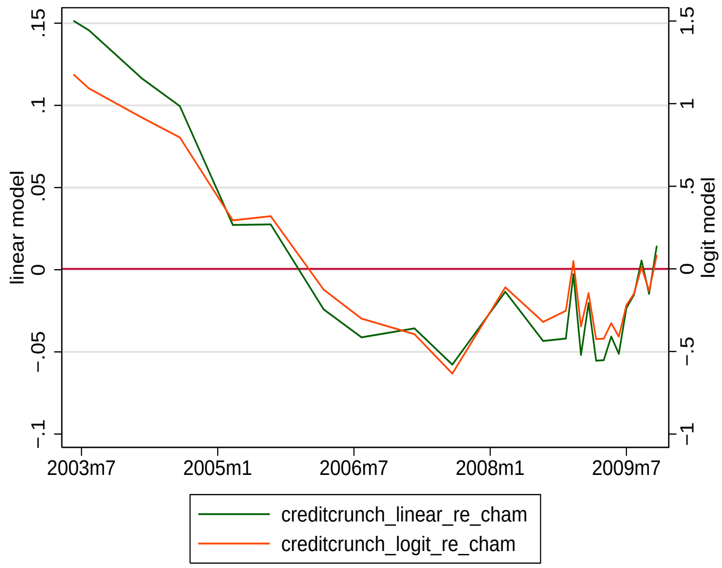


credit crunch indicator resulting from a correlated random effects logit model (depicted on the right axis), shows that both indicators evolve similarly over time.[4] In the case of the linear model, the credit crunch indicator reveals that for a given quality of firms and given refinancing costs of banks the probability of a restrictive credit supply was more than 10 percentage points higher in 2003 than by the end of the year 2009, where the credit crunch indicator is close to zero.

An explanation for the result that the credit crunch was more pronounced at the beginning of the decade than during the latest financial crisis can be given with the help of Figure 4, which shows the average shares of the negative responses to the survey questions across firms over time and the refinancing costs. Both periods of economic downturn are characterized by a quite similar pattern. A large share of firms assesses the banks' willingness to lend as restrictive, and at the same time many firms report a poor state of their business and more

[4]Our results are also robust across models with alternative assumptions about the distribution function F, see Appendix C.

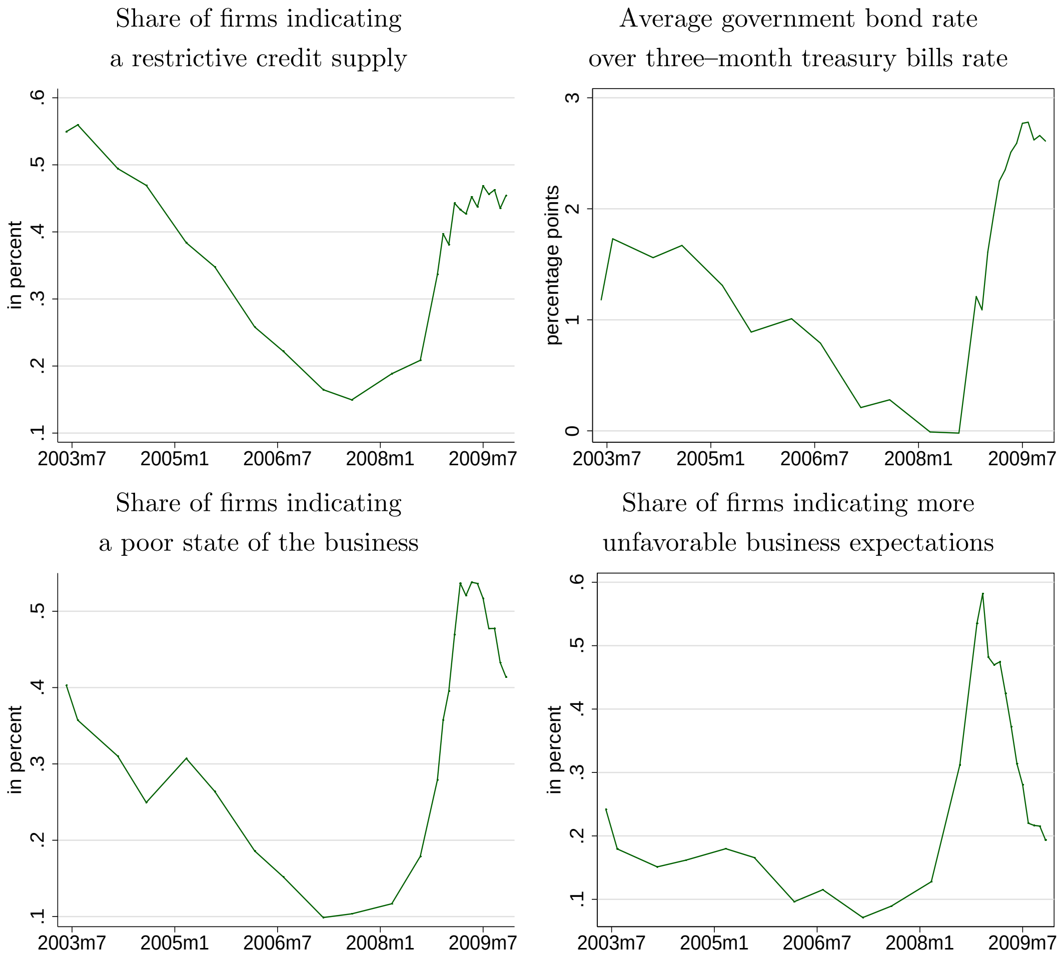
Figure 3: Credit Crunch Indicator (Logit and Linear Model)



unfavorable business expectations for the next six months. Moreover, interest rate spreads are higher than during boom times. A comparison of both periods shows, however, that despite the fact that both, the average quality of firms and the refinancing situation was better in 2003 than in 2009, the share of firms indicating a restrictive credit supply was about 10 percentage points higher in 2003 than in 2009. And it is exactly this gap that is reflected by the credit crunch indicator.

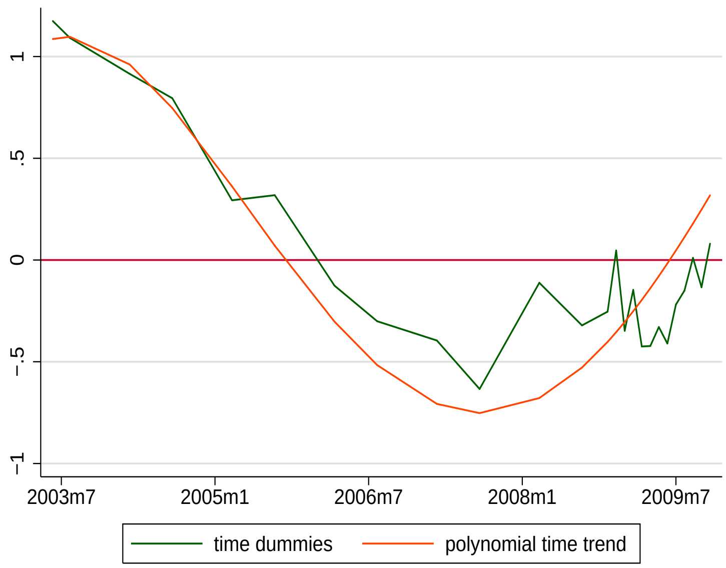
The two–step procedure for calculating the credit crunch indicator is required since the interest rate spread i_t and the time dummies t_{yymm} cannot be simultaneously used as regressors in the first–stage regression due to collinearities. The reason for this is simply that the T observations for the interest rate spread are identical to all firms, implying that their information is entirely captured by the time dummies. One way of avoiding the two–step procedure is to replace the $T-1$ time dummies in regression (3) by a higher–degree polynomial that best possibly reproduces the evolution of the estimated time dummy coefficients. In order to get an idea of how lending policies vary over the business cycle over and

Figure 4: Determinants of the Credit Crunch Indicator



above the quality assessment of the loan officer, we looked at the estimates of the time dummy coefficients in Figure 1 and decided to estimate the time trend of the variation of lending policies by a fourth degree polynomial. We then included both, the polynomial and the refinancing costs (labeled 'refinancing'), as non–firm–specific regressors in our non–linear panel model (3) and derived the credit crunch indicator directly from the estimated coefficients of the polynomial (see Table 8 in Appendix A for the regression results). Figure 5 shows that the resulting credit crunch indicator of the one–step procedure using a polynomial time trend evolves similarly to the credit crunch indicator resulting

Figure 5: Credit Crunch Indicator (Correlated Random Effects Logit Model)



from the two–step approach (see Figure 10 in Appendix A for the credit crunch indicators resulting under different model assumptions).

4 On the Role of Firm Size and Bank Relationships

The size of a firm is often viewed as an important determinant of a firm's access to credit. According to the bank lending view, which highlights the response of the supply of bank loans in the transmission of monetary policy, financial markets are characterized by imperfections and bank assets (loans, securities) are imperfect substitutes (Bernanke and Gertler, 1995). In the empirical literature, the relevance of the bank lending channel has been a controversial issue, due to the problem of identifying shifts in the supply of bank loans. In order to address the identification problem, several studies have considered disaggregated data and found that, following a monetary contraction, bank credit to small firms is reduced more than bank credit to large firms (see for example Gertler and Gilchrist, 1994, and Gilchrist and Zakrajsek, 1995). The main reason for this result is that small firms are more dependent on bank credit as they hardly have access to alternative financing sources, such as financial markets.

In order to analyze whether the size of firms has any influence on our credit crunch indicator, we included a dummy variable into the micro–econometric model that takes a value of 1, if a firm has 250 employees and more, and 0 otherwise. The information about the number of employees is also taken from the Ifo Business Survey. Table 4 shows that roughly two thirds of the firms in our sample are classified as small according to this definition. Since we are mainly interested in the variation of lending policies over time we additionally introduced a set of interaction terms by multiplying the time dummies with the firm size dummy.

Table 4: Descriptive Statistics

	mean(credit)	N
Firm size		
$<$ 250 employees	0.39	37188
$\geq$ 250 employees	0.38	19758
Bank relationship		
savings banks	0.38	11484
landes banks	0.42	1755
credit cooperatives	0.35	5108
private commercial banks	0.36	12156
other banks	0.39	3510

Another interesting issue is whether the category of bank, with which the firm is primarily negotiating credits, has any influence on the firm's assessment of credit supply. A peculiarity of the German banking system is its three–pillar structure based on private commercial banks, banks governed by public law and credit cooperatives. The private commercial banks include major banks such as Deutsche Bank and Commerzbank; banks governed by public law are the roughly 500 "Sparkassen" (savings banks) and the "Landesbanken" (landes banks); cooperative banks include the roughly 1200 "Volks– und Raiffeisenbanken" and their two central institutions DZ Bank and WGZ–Bank. During the financial crisis in particular the state–owned landes banks and some of the large private commercial banks have been hard hit, while both savings banks and cooperative banking institutions turned out to be relatively stable.

In a special question that was included in the questionnaire of the Ifo Business Survey in June 2009, firms were asked about the category of bank, with which they are predominantly negotiating credits. The answers to choose from were "savings banks", "landes banks", "credit cooperatives", "private commercial banks" and "other banks". We assumed that the firms have had the same bank relationship over the entire sample period[5] and constructed four dummy variables (control group = savings banks), which was introduced in the micro–econometric model as a set of interaction terms by multiplying the time dummies with the four bank dummies. Table 4 shows that the information about the bank relationship is available for about 60 percent of the observations in our sample.

The results of both regressions with interaction terms are shown in Table 5. In this Section we only applied the correlated random effects model since there is significant panel heterogeneity and the estimates of the correlated random effects model turned out to be very close to those of the fixed effects model (see Table 3, columns 4 and 5). Moreover, we can avoid the loss of almost 13000 observations, which is related to the conditional maximum likelihood estimation of the fixed effects model. Since we only allowed the firm size dummy and the bank relationship dummy to interact with the time dummies, the coefficients on the firm–specific regressors are identical across groups. As in the baseline regression the coefficients of the state of the business, the business expectations and the sector–specific business climate are significant and have the correct negative sign. The coefficients on the time dummies are shown separately for each subgroup. For both regressions, the first column shows the coefficients on the time dummies of the control group, i.e. small firms in the model with firm size interaction and savings banks in the model with bank relationship

[5]It is common practice in credit financing for close ties to exist between firms and banks. One of the countries where relationship lending is supposed to be especially prevalent is Germany, often cited as the classical example of a bank–based system with strong customer–borrower–relationships (Elsas and Krahnen, 1998). An important indicator to measure relationship lending is the duration of a bank–borrower relationship (Petersen and Rajan, 1994). According to survey evidence the average duration of bank relationships in Germany lies between 15 and 20 years (Elsas, 2005).

Table 5: Results with Interactions

	Interaction with firm size		Interaction with bank relationship				
	< 250 ee	≥ 250 ee	savings	landes	credit	private	other
statebus	0.420***				0.495***		
	(16.76)				(15.38)		
comexp	0.130***				0.099**		
	(5.53)				(3.28)		
statebus_mbank	1.209***				1.030***		
	(13.14)				(7.22)		
comexp_mbank	0.041				0.059		
	(0.39)				(0.34)		
climatesector	-0.007***				-0.006***		
	(-4.89)				(-3.32)		
dummy_group		-0.852***		-0.884	0.441	-0.650**	-1.036**
		(-6.62)		(-1.83)	(1.32)	(-2.71)	(-2.90)
t_0308	0.151	0.013	0.217	1.249*	-0.110	0.038	-0.074
	(1.52)	(0.08)	(1.08)	(2.13)	(-0.27)	(0.14)	(-0.17)
t_0403	-0.118	-0.192	-0.073	0.168	-0.651	-0.198	0.433
	(-1.19)	(-1.19)	(-0.37)	(0.30)	(-1.70)	(-0.72)	(1.04)
t_0408	-0.141	-0.333*	-0.219	0.634	-0.309	-0.266	0.305
	(-1.37)	(-1.99)	(-1.08)	(1.13)	(-0.79)	(-0.94)	(0.72)
t_0503	-0.794***	-0.403*	-0.789***	0.396	-0.400	-0.321	0.066
	(-7.91)	(-2.40)	(-3.98)	(0.70)	(-1.05)	(-1.16)	(0.15)
t_0508	-1.062***	-0.259	-1.225***	0.920	-0.279	0.047	0.515
	(-10.34)	(-1.49)	(-6.11)	(1.67)	(-0.72)	(0.17)	(1.20)
t_0603	-1.553***	-0.411*	-1.841***	0.773	-0.008	-0.003	0.937*
	(-13.73)	(-2.24)	(-8.65)	(1.34)	(-0.02)	(-0.01)	(2.21)
t_0608	-1.860***	-0.404*	-2.128***	0.439	-0.458	0.238	0.775
	(-15.92)	(-2.02)	(-9.72)	(0.72)	(-1.12)	(0.79)	(1.71)
t_0703	-2.302***	-0.475*	-2.537***	0.592	-0.381	0.321	0.798
	(-18.31)	(-2.22)	(-11.11)	(0.97)	(-0.93)	(1.04)	(1.75)
t_0708	-2.631***	0.107	-3.185***	0.431	0.237	0.922**	1.431**
	(-20.19)	(0.49)	(-12.93)	(0.60)	(0.55)	(2.83)	(3.00)
t_0803	-2.343***	0.489*	-3.015***	1.742**	0.256	1.139***	1.524***
	(-19.15)	(2.54)	(-13.13)	(3.02)	(0.63)	(3.76)	(3.48)
t_0808	-2.419***	0.473*	-2.640***	0.531	-0.525	0.520	1.176**
	(-21.41)	(2.49)	(-12.66)	(0.89)	(-1.32)	(1.78)	(2.76)
t_0811	-2.002***	1.689***	-2.185***	1.831***	-0.400	1.108***	2.024***
	(-18.50)	(9.64)	(-11.00)	(3.42)	(-1.05)	(4.06)	(5.13)
t_0812	-1.698***	1.658***	-1.725***	1.984***	-0.907*	1.038***	1.432***
	(-14.82)	(9.18)	(-8.42)	(3.65)	(-2.34)	(3.75)	(3.53)
t_0901	-1.793***	1.587***	-1.875***	2.128***	-1.037**	0.980***	1.401***
	(-16.50)	(9.22)	(-9.53)	(3.96)	(-2.71)	(3.65)	(3.57)
t_0902	-1.454***	1.782***	-1.503***	1.862***	-0.754*	1.074***	1.726***
	(-13.36)	(10.31)	(-7.65)	(3.51)	(-2.03)	(4.02)	(4.38)
t_0903	-1.537***	1.737***	-1.523***	1.824***	-0.900*	0.912***	1.832***
	(-14.35)	(10.17)	(-7.85)	(3.48)	(-2.44)	(3.47)	(4.67)
t_0904	-1.501***	1.733***	-1.579***	1.486**	-0.637	0.903***	1.859***
	(-14.10)	(10.03)	(-8.21)	(2.81)	(-1.73)	(3.43)	(4.78)
t_0905	-1.358***	1.834***	-1.318***	1.364**	-0.798*	0.903***	1.608***
	(-12.82)	(10.60)	(-6.90)	(2.58)	(-2.18)	(3.46)	(4.14)
t_0906	-1.399***	1.791***	-1.314***	1.567**	-0.859*	0.961***	1.406***
	(-13.42)	(10.40)	(-7.12)	(3.05)	(-2.40)	(3.76)	(3.70)
t_0907	-1.116***	1.701***	-1.080***	1.426**	-0.630	0.963***	1.563***
	(-10.90)	(9.89)	(-5.78)	(2.71)	(-1.75)	(3.70)	(4.00)
t_0908	-1.055***	1.603***	-1.020***	1.925***	-0.746*	0.849**	1.499***
	(-10.23)	(9.19)	(-5.40)	(3.59)	(-2.04)	(3.22)	(3.84)
t_0909	-1.089***	1.853***	-0.876***	1.428**	-1.189**	0.742**	1.511***
	(-9.89)	(10.03)	(-4.48)	(2.64)	(-3.13)	(2.72)	(3.77)
t_0910	-1.189***	1.762***	-1.089***	1.666**	-0.759*	0.877***	1.283***
	(-11.63)	(10.18)	(-5.80)	(3.16)	(-2.08)	(3.36)	(3.29)
t_0911	-1.022***	1.741***	-1.096***	1.553**	-0.483	1.021***	1.589***
	(-9.89)	(9.98)	(-5.70)	(2.94)	(-1.32)	(3.85)	(4.02)
_cons	-3.517***				-3.366***		
	(-13.67)				(-7.85)		
lnsig2u							
_cons	1.664***				1.648***		
	(47.92)				(34.83)		
N	56946				34013		
AIC	51583.03				30457.26		
LogL	-2.6e+04				-1.5e+04		

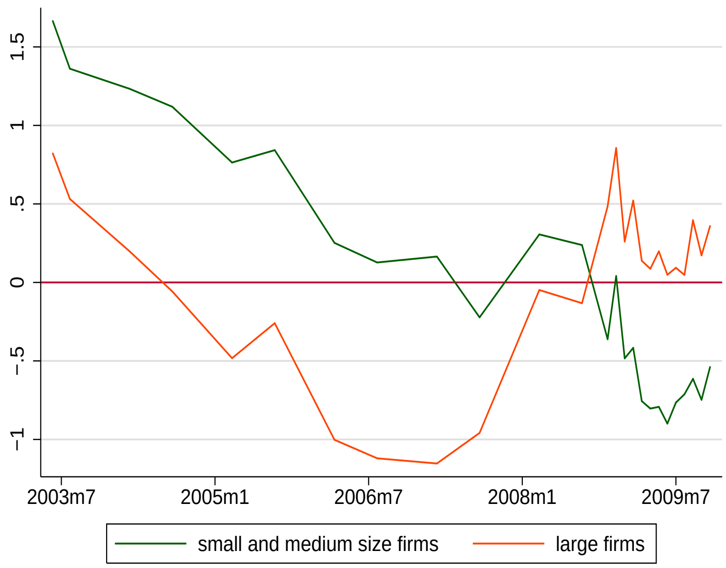
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

interaction. The columns to the right of the first column show a group–specific intercept term in the first row and the coefficients on the interaction terms for each subgroup in the rows below. The sum of the group intercept and the coefficients on the interaction terms tells us whether the willingness to lend for this subgroup at a certain point in time is greater or smaller than in the control group. We performed joint Wald tests for each subgroup and could reject the null hypothesis that the estimated interaction terms are zero.

The credit crunch indicator for each subgroup in the two models is computed as before. Instead, however, of running a single equation regression, we estimated a system of seemingly unrelated regression equations and restricted the coefficient on the interest rate spread to be the same across all subgroups. The following results stand out. First, while in the years before 2008 large firms faced much more favorable credit conditions than small firms, one of the characteristics of the latest financial crisis is that in particular large firms reported a more subdued willingness of the banks to grant credit (see Figure 6). Thus, large firms were likely to face a credit crunch in Germany, whereas the provision of credit for small businesses was perceived as ample, given the impaired creditworthiness of these firms and the large increase of financing premia on the capital markets.

Second, one of the reasons why large firms were more affected by the financial crisis than small firms has to do with the bank relationships that the firms maintain. Table 6 reveals that large firms typically demand credit from private commercial banks and landes banks, and hence from those banks that were mostly affected by the financial crisis in Germany. The customers of credit cooperatives and savings banks are almost exclusively small firms. Given this connection the credit crunch indicators derived from the model with bank relationship interaction gives a picture that is quite similar to that of the model with firm size interaction (see Figure 7). Before 2008 customers of private commercial banks and landes banks reported a less restrictive credit supply than customers of credit cooperatives and savings banks, given an identical quality of the firms and the same refinancing costs across banks. The situation changed with the financial crisis. Our results indicate that in 2009 mainly customers of landes banks and private commercial banks were affected by adverse credit

Figure 6: Credit Crunch Indicator (Firm Size)



conditions, while small firms that are getting loans from credit cooperatives and savings banks reported a much better credit market situation.

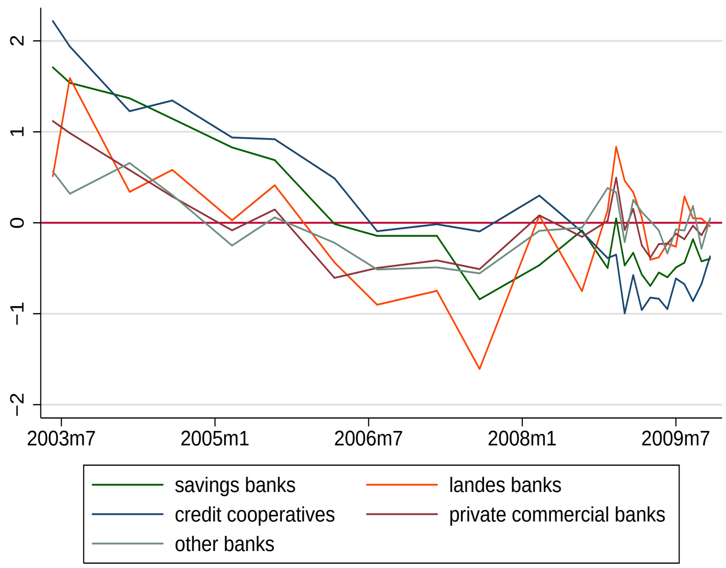
Table 6: Bank Relationship and Firm Size

Bank relationship	share of large firms
savings banks	22%
landes banks	41%
credit cooperatives	11%
private commercial banks	50%
other banks	51%

Notes: In the special question of the Ifo Business Survey in June 2009 about the firms' bank relationships 60% of the firms in our sample provided the requested information about the main lender. For each banking group the Table shows the share of large firms.

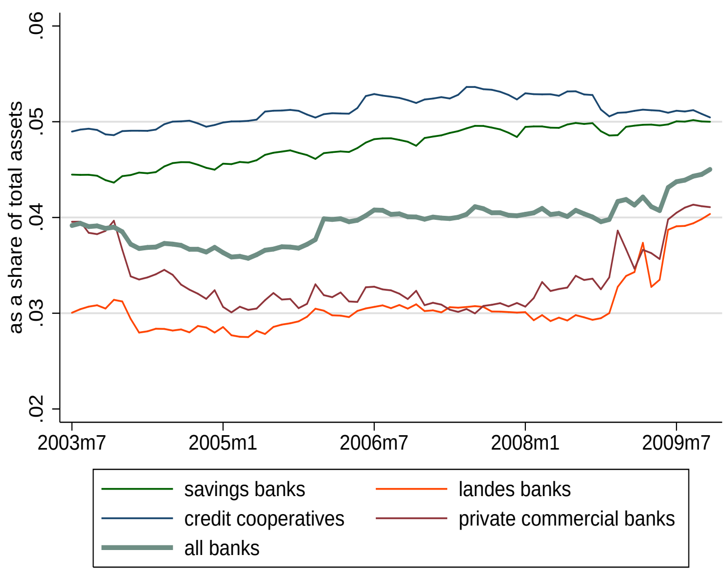
An explanation for the result that the situation during the financial crisis was so different from the situation in 2003/2004 can be given by the evolution of the banks' capital ratio. An important factor which may lead to a contraction

Figure 7: Credit Crunch Indicator (Bank Relationship)



in credit supply is related to the difficulties that banks encounter on the liability side of their balance sheet and, in particular, in maintaining an adequate level of capital, be it connected with prudential regulation or market discipline. This is the reason why the label capital crunch is often used synonymously with a credit crunch (Bernanke and Lown, 1991). Figure 8 shows that the banks' capital ratio, and mainly that of private commercial banks, was declining in the years 2003 and 2004. However, during the financial crisis capital ratios do not seem to impose any restrictions on the lending activity of banks, as the share of capital in total assets increased from 4% in the beginning of 2008 to about 4.5% by the end of 2009. This increase, which is mainly due to the crisis–hit private commercial banks and landes banks, can be explained by the massive public sector equity support to banks. In October 2008 the Financial Markets Stabilization Fund was established in Germany, with the purpose of stabilizing the financial market by overcoming liquidity shortages and by creating the framework conditions for a strengthening of the capital base of financial–sector institutions. Among the various instruments, the Fund participates in the recapitalization of financial–

Figure 8: Banks' Capital



sector enterprizes, which amounted to 25 billions of euros until the end of 2009, and hence to approximately 0.6% of average total assets of private commercial banks and landes banks in 2009.

5 Conclusion

This paper presents a micro data approach to the identification of credit crunches. Using a survey among German firms which regularly queries the firms' assessment of the current willingness of banks to extend credit we estimate the probability of a restrictive credit supply policy by time taking into account the creditworthiness of borrowers. Creditworthiness is approximated by firm–specific factors, e.g. the firms' assessment of their current business situation and their business expectations for the next six months. After controlling for the banks' refinancing costs, which are also likely to affect the supply of loans, we derive a credit crunch indicator, which measures that part of the shift in the willingness to lend that is neither explained by firm-specific factors nor by refinancing costs.

Our results show that the probability of a credit crunch in the German economy was high in the years 2003 to 2005, following the economic downturn after the burst of the New Economy Bubble. In the subsequent boom of the years 2006 to 2008 the credit supply of banks was very lax. Even after controlling for the on average good quality of the firms and the low level of refinancing costs, the banks' willingness to lend was perceived as accommodating. Most surprisingly, in the financial crisis, in which banks were much more involved than in previous recessions due to massive write–downs of toxic assets, the indications of a credit crunch are rather weak. Only large firms that mainly negotiate credits with state–owned landes banks reported a subdued willingness of the banks to grant credit, which can neither be explained by the impaired creditworthiness of these firms, nor by the large increase of financing premia on the capital markets.

References

ABBERGER, K., M. BIRNBRICH, AND C. SEILER (2009): "Der 'Test des Tests' im Handel – eine Metaumfrage zum ifo Konjunkturtest," *ifo Schnelldienst*, 62(21), 34–41.

ALBERTAZZI, U., AND D. J. MARCHETTI (2010): "Credit Crunch, Flight to Quality and Evergreening: An Analysis of Bank-Firm Relationships After Lehman," Working paper, Banca d'Italia.

BAUM, C. F., M. E. SCHAFFER, AND S. STILLMAN (2010): "IVREG29: Stata module for extended instrumental variables/2SLS and GMM estimation (v9)," Statistical Software Components, Boston College Department of Economics.

BERNANKE, B., AND M. GERTLER (1995): "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *The Journal of Economic Perspectives*, 9(4), 27–48.

BERNANKE, B., AND C. LOWN (1991): "The Credit Crunch," *Brookings Papers on Economic Activity*, 1991(2), 205–247.

BERNANKE, B. S. (1983): "Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression," *American Economic Review*, 73(3), 257–76.

BERNANKE, B. S., AND A. S. BLINDER (1992): "The Federal Funds Rate and the Channels of Monetary Transmission," *American Economic Review*, 82(4), 901–21.

BORENSZTEIN, E., AND J.-W. LEE (2002): "Financial Crisis and Credit Crunch in Korea: Evidence from Firm–level Data," *Journal of Monetary Economics*, 49(4), 853–875.

BOUND, J., D. JAEGER, AND R. BAKER (1995): "Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variables is Weak," *Journal of the American Statistical Association*, 90(430), 443–450.

Cameron, A. C., and P. K. Trivedi (2009): *Microeconometrics Using Stata*. StataCorp LP.

Chamberlain, G. (1980): "Analysis of Covariance with Qualitative Data," *The Review of Economic Studies*, 47(1), 225–238.

——— (1984): "Panel Data," in *Handbook of Econometrics (Volume II)*, ed. by Z. Griliches, and M. Intriligator, pp. 1247–1318, Amsterdam. North Holland.

Ding, W., I. Domac, and G. Ferri (1998): "Is there a Credit Crunch in East Asia?," Policy Research Working Paper Series 1959, The World Bank.

Elsas, R. (2005): "Empirical Determinants of Relationship Lending," *Journal of Financial Intermediation*, 14(1), 32–57.

Elsas, R., and J. P. Krahnen (1998): "Is Relationship Lending Special? Evidence from Credit–file Data in Germany," *Journal of Banking and Finance*, 22(10-11), 1283–1316.

Gertler, M., and S. Gilchrist (1994): "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109(2), 309–340.

Gilchrist, S., and E. Zakrajsek (1995): "The Importance of Credit for Macroeconomic Activity: Identification through Heterogeneity," in *Conference Series of the Federal Reserve Bank of Boston*, vol. 39, pp. 129–158. Federal Reserve Bank of Boston.

Hsiao, C. (2003): *Analysis of panel data*. Cambridge Univ Press.

Kashyap, A. K., O. A. Lamont, and J. C. Stein (1994): "Credit Conditions and the Cyclical Behavior of Inventories," *The Quarterly Journal of Economics*, 109(3), 565–92.

Kashyap, A. K., and J. C. Stein (1995): “The Impact of Monetary Policy on Bank Balance Sheets,” *Carnegie-Rochester Conference Series on Public Policy*, 42(1), 151–195.

Kashyap, A. K., J. C. Stein, and D. W. Wilcox (1993): “Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance,” *American Economic Review*, 83(1), 78–98.

Mundlak, Y. (1978): “On the Pooling of Time Series and Cross Section Data,” *Econometrica*, 46(1), 69–85.

Nelson, C. R., and R. Startz (1990): “Some Further Results on the Exact Small Sample Properties of the Instrumental Variable Estimator,” *Econometrica*, 58(4), 967–76.

Oliner, S. D., and G. D. Rudebusch (1996): “Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance: Comment,” *American Economic Review*, 86(1), 300–309.

Peek, J., and E. Rosengren (1995): “Bank Regulation and the Credit Crunch,” *Journal of Banking and Finance*, 19(3-4), 679–692.

Peek, J., and E. S. Rosengren (2000): “Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States,” *American Economic Review*, 90(1), 30–45.

Petersen, M. A., and R. G. Rajan (1994): “The Benefits of Lending Relationships: Evidence from Small Business Data,” *Journal of Finance*, 49(1), 3–37.

Schaffer, M. E. (2005): “XTIVREG2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models,” Statistical Software Components, Boston College Department of Economics.

Staiger, D., and J. H. Stock (1997): “Instrumental Variables Regression with Weak Instruments,” *Econometrica*, 65(3), 557–586.

Stock, J. H., and M. Yogo (2002): "Testing for Weak Instruments in Linear IV Regression," NBER Technical Working Papers 0284, National Bureau of Economic Research, Inc.

Udell, G. (2009): "How Will a Credit Crunch Affect Small Business Finance?," *FRBSF Economic Letter*, 2009, 1–3.

Woo, D. (2003): "In Search of 'Capital Crunch': Supply Factors behind the Credit Slowdown in Japan," *Journal of Money, Credit and Banking*, 35(6), 1019–1038.

Appendices

A Regression Results (Robustness)

Table 7: Results of the Linear Model

	(1) linear	(2) linear_re	(3) linear_re_cham	(4) linear_fe	(5) linear_iv	(6) linear_iv_fe
statebus	0.122***	0.073***	0.062***	0.061***	0.172***	0.071***
	(20.53)	(16.23)	(13.09)	(12.96)	(5.20)	(4.16)
comexp	0.027***	0.017***	0.016***	0.015***	-0.006	-0.016
	(4.79)	(4.59)	(4.03)	(3.88)	(-0.27)	(-0.81)
climatesector	-0.002***	-0.002***	-0.002***	-0.002***	-0.001*	-0.002***
	(-4.33)	(-5.31)	(-5.27)	(-4.63)	(-2.39)	(-6.19)
t_0308	0.033***	0.027**	0.027**	0.026**	0.027*	0.021
	(3.30)	(2.87)	(2.84)	(2.68)	(2.46)	(1.65)
t_0403	-0.011	-0.012	-0.012	-0.012	-0.014	-0.014
	(-0.94)	(-1.05)	(-1.07)	(-1.03)	(-1.04)	(-1.03)
t_0408	-0.018	-0.022	-0.023	-0.023	-0.021	-0.030*
	(-1.39)	(-1.74)	(-1.82)	(-1.83)	(-1.42)	(-2.13)
t_0503	-0.121***	-0.117***	-0.116***	-0.113***	-0.128***	-0.124***
	(-9.53)	(-9.60)	(-9.58)	(-9.07)	(-8.86)	(-9.11)
t_0508	-0.148***	-0.141***	-0.141***	-0.139***	-0.149***	-0.148***
	(-11.27)	(-11.33)	(-11.31)	(-10.78)	(-10.02)	(-10.85)
t_0603	-0.182***	-0.184***	-0.186***	-0.186***	-0.189***	-0.190***
	(-10.60)	(-11.37)	(-11.46)	(-10.91)	(-9.75)	(-12.65)
t_0608	-0.211***	-0.214***	-0.216***	-0.215***	-0.204***	-0.217***
	(-12.49)	(-13.46)	(-13.58)	(-12.89)	(-10.44)	(-14.84)
t_0703	-0.237***	-0.241***	-0.245***	-0.245***	-0.222***	-0.239***
	(-12.65)	(-13.84)	(-14.01)	(-13.22)	(-10.12)	(-15.34)
t_0708	-0.262***	-0.259***	-0.263***	-0.261***	-0.253***	-0.262***
	(-14.80)	(-15.72)	(-15.91)	(-14.91)	(-12.07)	(-17.20)
t_0803	-0.236***	-0.233***	-0.235***	-0.233***	-0.220***	-0.222***
	(-14.45)	(-14.89)	(-15.05)	(-14.08)	(-11.11)	(-14.95)
t_0808	-0.275***	-0.265***	-0.266***	-0.261***	-0.251***	-0.246***
	(-21.67)	(-21.39)	(-21.44)	(-20.07)	(-13.16)	(-16.20)
t_0811	-0.214***	-0.193***	-0.191***	-0.184***	-0.180***	-0.162***
	(-15.28)	(-14.21)	(-14.08)	(-12.96)	(-8.00)	(-9.01)
t_0812	-0.183***	-0.163***	-0.159***	-0.152***	-0.147***	-0.125***
	(-11.47)	(-10.88)	(-10.64)	(-9.68)	(-6.19)	(-6.62)
t_0901	-0.204***	-0.182***	-0.178***	-0.170***	-0.176***	-0.149***
	(-13.49)	(-12.45)	(-12.16)	(-11.08)	(-8.62)	(-9.16)
t_0902	-0.157***	-0.132***	-0.126***	-0.118***	-0.140***	-0.106***
	(-9.91)	(-8.63)	(-8.28)	(-7.39)	(-7.05)	(-6.76)
t_0903	-0.180***	-0.148***	-0.143***	-0.134***	-0.170***	-0.126***
	(-11.63)	(-9.96)	(-9.57)	(-8.50)	(-9.11)	(-8.22)
t_0904	-0.174***	-0.142***	-0.137***	-0.128***	-0.166***	-0.120***
	(-11.57)	(-9.76)	(-9.37)	(-8.35)	(-9.21)	(-8.22)
t_0905	-0.149***	-0.118***	-0.113***	-0.104***	-0.134***	-0.090***
	(-9.97)	(-8.15)	(-7.77)	(-6.83)	(-7.70)	(-6.36)
t_0906	-0.158***	-0.124***	-0.119***	-0.110***	-0.154***	-0.104***
	(-10.98)	(-8.87)	(-8.48)	(-7.48)	(-9.34)	(-7.60)
t_0907	-0.113***	-0.085***	-0.080***	-0.073***	-0.115***	-0.070***
	(-8.24)	(-6.37)	(-6.01)	(-5.20)	(-7.33)	(-5.21)
t_0908	-0.105***	-0.075***	-0.071***	-0.064***	-0.107***	-0.063***
	(-7.73)	(-5.69)	(-5.38)	(-4.64)	(-6.84)	(-4.65)
t_0909	-0.094***	-0.064***	-0.060***	-0.053***	-0.103***	-0.056***
	(-6.44)	(-4.59)	(-4.31)	(-3.62)	(-6.14)	(-3.91)
t_0910	-0.109***	-0.082***	-0.078***	-0.071***	-0.108***	-0.068***
	(-8.10)	(-6.11)	(-5.84)	(-5.07)	(-6.96)	(-5.04)
t_0911	-0.078***	-0.055***	-0.052***	-0.046**	-0.081***	-0.041**
	(-5.63)	(-4.06)	(-3.82)	(-3.22)	(-5.00)	(-2.88)
statebus_m			0.142***			
			(12.37)			
comexp_m			0.003			
			(0.23)			
_cons	0.183***	0.307***	0.019	0.319***	0.131*	
	(9.74)	(19.66)	(0.63)	(19.33)	(2.03)	
N	56946	56946	56946	56946	43146	42833
AIC	74198.38	.	.	41008.76	56122.64	29738.73
R^2	0.091	.	.	0.095	0.086	0.094

t statistics, which are shown in parentheses, are robust to heteroskedasticity and, in the case of the pooled models (1) and (5), clustering on individual firms.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Regression with Time Trend (Logit and Linear Model)

	(1) logit	(2) logit_re	(3) logit_re_cham	(4) logit_fe	(5) linear	(6) linear_re	(7) linear_re_cham	(8) linear_fe
statebus	0.562***	0.554***	0.466***	0.455***	0.122***	0.072***	0.061***	0.061***
	(19.85)	(23.38)	(19.02)	(18.54)	(20.63)	(24.01)	(19.49)	(13.00)
comexp	0.127***	0.143***	0.131***	0.130***	0.027***	0.017***	0.016***	0.015***
	(5.00)	(6.36)	(5.69)	(5.65)	(4.79)	(5.86)	(5.16)	(3.93)
climatesector	-0.007***	-0.013***	-0.014***	-0.013***	-0.001***	-0.001***	-0.002***	-0.001***
	(-6.15)	(-12.87)	(-13.15)	(-12.09)	(-5.19)	(-11.40)	(-11.71)	(-7.25)
t	0.011	0.018	0.019	0.020	-0.001	-0.001	-0.000	0.000
	(1.31)	(1.58)	(1.66)	(1.70)	(-0.83)	(-0.32)	(-0.21)	(0.04)
t^2	-0.002***	-0.004***	-0.004***	-0.004***	-0.000**	-0.000***	-0.000***	-0.000***
	(-4.27)	(-5.41)	(-5.50)	(-5.40)	(-2.77)	(-3.87)	(-3.98)	(-3.80)
t^3	0.000***	0.000***	0.000***	0.000***	0.000**	0.000***	0.000***	0.000***
	(3.64)	(5.08)	(5.19)	(5.13)	(2.59)	(3.99)	(4.11)	(3.75)
t^4	-0.000*	-0.000***	-0.000***	-0.000***	-0.000	-0.000**	-0.000**	-0.000**
	(-2.48)	(-3.81)	(-3.95)	(-3.94)	(-1.71)	(-3.06)	(-3.19)	(-2.86)
refinancing	0.103***	0.237***	0.250***	0.260***	0.023***	0.030***	0.032***	0.032***
	(3.67)	(6.12)	(6.46)	(6.66)	(3.92)	(6.38)	(6.78)	(5.94)
statebus_m			1.165***				0.142***	
			(12.86)				(13.18)	
comexp_m			0.018				0.003	
			(0.17)				(0.24)	
_cons	-1.584***	-1.821***	-4.216***		0.175***	0.283***	-0.010	0.288***
	(-18.05)	(-18.78)	(-16.74)		(9.27)	(22.02)	(-0.34)	(17.12)
lnsig2u								
_cons		1.660***	1.635***					
		(47.74)	(46.93)					
N	56946	56946	56946	44041	56946	56946	56946	56946
AIC	70452.63	52800.07	52617.48	32714.27	74218.53	.	.	41046.10
LogL	-3.5e+04	-2.6e+04	-2.6e+04	-1.6e+04	-3.7e+04	.	.	-2.1e+04

t statistics, which are shown in parentheses, are robust to heteroskedasticity in the case of the linear models and, in the case of the linear pooled model (5), clustering on individual firms.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Instrumental Variable Regression

In order to account for the potential endogeneity of the regressors *statebus* and *comexp*, we estimate both the pooled and the fixed effects linear probability model with IV methods (see the last two columns (5) and (6) in Table 7 in Appendix A).[6] As instruments we use five lags of an additional variable, *proexp*, which is also taken out of the Ifo Business Survey and which measures the survey respondents expectations about their domestic production in the next three months. Similar to *statebus* and *comexp*, *proexp* is an ordinal variable with three categories, "increasing", "unchanged" and "decreasing". Since the dependent variable *credit* is binary, the error term is heteroscedastic and we calculate heteroscedasticity–robust standard errors. To test the validity of our overidentifying restrictions we calculate Hansen's J–statistic, which is 1.92 (1.02) in the case of the pooled (fixed effects) model. With 3 degrees of freedom this

[6] The IV regressions were performed using the Stata commands ivreg2 and xtivreg2, written by Schaffer (2005) and Baum, Schaffer, and Stillman (2010).

results in a p–value of 0.589 (0.796), implying that we cannot reject the null hypothesis that all instruments are valid.

The exogeneity of *statebus* and *comexp* is addressed using a C–test. If *statebus* and *comexp* are exogenous, we can additionally use these variables as their own instruments. Since the moments used in the IV approaches are strict subsets of the instruments used in the exogenous case, the validity of the additional instruments can be tested by a Sargan (Hansen) difference test. The C–statistic for the pooled (fixed effects) model is 3.28 (2.54) with 2 degrees of freedom resulting in a p–value of 0.194 (0.281). So we cannot reject at every usual significance level the null hypothesis that *statebus* and *comexp* are exogenous.

An additional issue in IV regressions is the weakness of the instruments. If instruments are weak, the estimates are biased even in large but finite samples and the estimated standard errors are too small, leading to size distortions of the significance tests for endogenous regressors (Nelson and Startz, 1990; Bound, Jaeger, and Baker, 1995; Staiger and Stock, 1997). In order to address these problems, we perform weak instruments tests proposed by Stock and Yogo (2002). Our null hypothesis is that the instruments are weak, in the sense that the maximal relative bias of the IV estimation in relation to OLS and the maximal size distortion are unacceptably large. When we choose 5% for the maximal relative bias and do not tolerate an actual test size greater than 10%, we can reject the null hypothesis of weak instruments for both, the pooled and the fixed effects model.

To sum up, the tests show that there is no evidence of weak or endogenous instruments. Furthermore, we cannot reject the null hypothesis that *statebus* and *comexp* are exogenous.

C Credit Crunch Indicator (Robustness)

Figure 9: Credit Crunch Indicator (Linear Model)

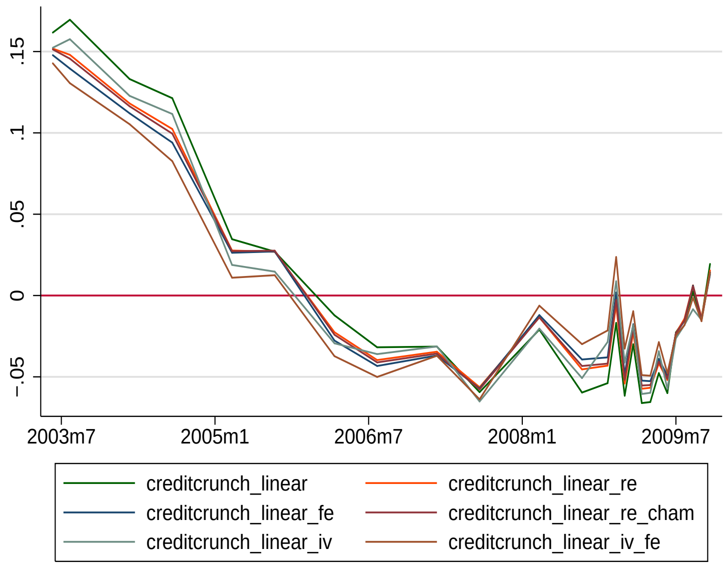
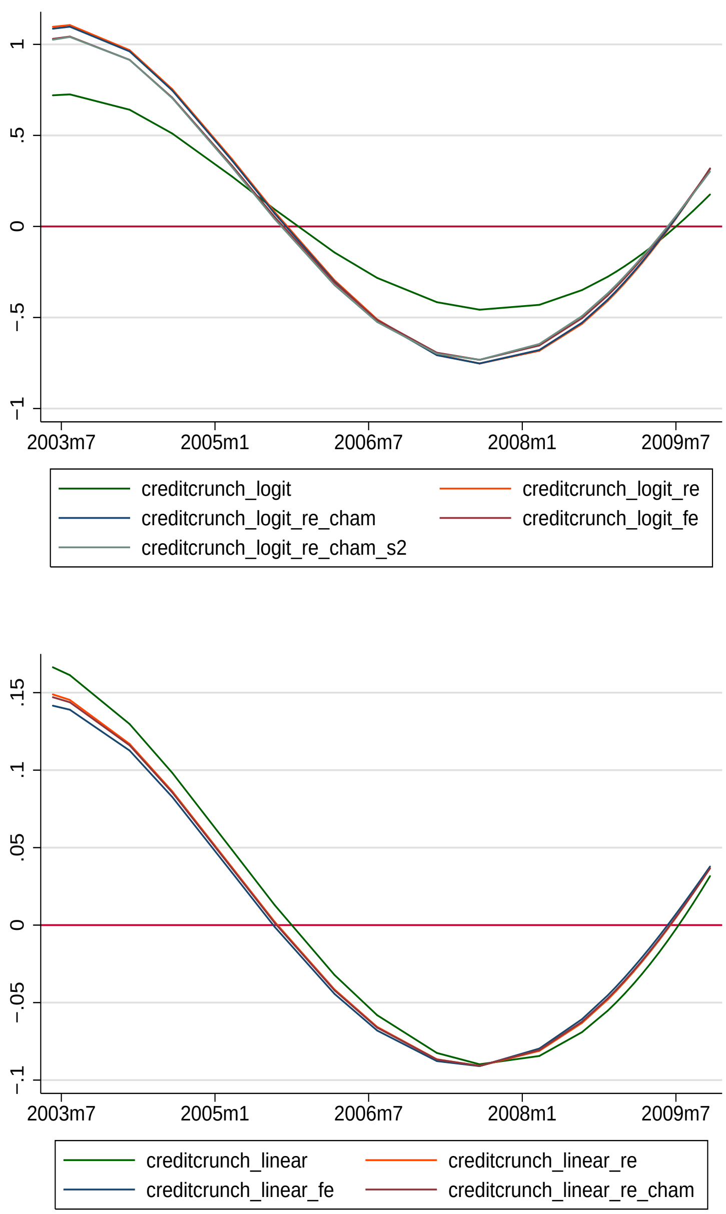


Figure 10: Credit Crunch Indicator with Time Trend (Logit and Linear Model)



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